

# **Individual Heterogeneity in Loss Aversion and Its Impact on Social Security Claiming Decisions**

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## **Abstract:**

We begin by documenting the development of an easy to use, model free, measure of loss aversion based on responses to pairs of mixed (gain and loss) three-outcome gambles. This measure is tested using surveys with a cumulative total of more than 7000 respondents of pre-retirement age. We show that the measure has both internal validity and external validity. Specifically, the results fit well with data from other loss aversion research and are correlated with respondent demographics in reasonable ways. We test external validity by showing that the measure predicts consumer financial preferences for retirement savings investments, Social Security claiming, and life annuity preferences. Using these findings, we hope to continue to develop decision tools and interventions that are targeted based on individual heterogeneity in measures such as loss aversion.

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## 1. Introduction

Many of the complex, and difficult, consumer financial decisions we face such as choices for mortgages, health insurance, and when to collect Social Security benefits involve options that have multiple “mixed” outcomes in the sense that there is both risk of loss and opportunity for gain. A key concept in explaining such decisions is loss aversion. Kahneman (2011) defines loss aversion in terms of the direct comparison of gains with losses - the idea that “losses loom larger than gains” - and makes it clear that individuals will differ in their loss aversion. For marketers of financial services, or public policy experts who may wish to nudge individuals’ risky decisions, having a simple and easy to use individual loss aversion measure is useful for customizing their advice.

In this paper, we report on the results of a set of analyses that test a new measure of loss aversion with over 7,000 participants from online studies with national survey panel companies. All of the results presented are for respondents whose choices satisfy first-order stochastic dominance. We focus on four main questions: (1) whether the individual measures of loss aversion collected from participants match the typical overall distribution of loss aversion found in other studies; (2) how individual loss aversion measures correlate with other individual differences such as gender, age, and time preferences; (3) whether these measures are predictive of other behaviors and choices, especially within the realm of Social Security claiming decisions; and (4) the predictive power of our loss aversion measure relative to traditional measures of risk taking.

To summarize our results, we find that the overall pattern of loss aversion scores we collected is consistent with the results found in other studies. We check robustness by testing the measure with different probability values; the similarity in responses across different probability

amounts suggests that respondents are focusing on comparisons between gain and loss amounts and not simply expected value differences. Next, we find that other individual differences are correlated with our loss aversion measure in meaningful ways, such as females indicating higher loss aversion. More importantly, we find that this choice-based loss aversion measure is highly predictive of a range of expressed preferences for financial decisions. For example, we consistently find that higher levels of loss aversion predict individuals' preference for claiming Social Security benefits early. We also find that loss aversion is predictive of decisions about retirement savings, life annuities, and investment preferences, such choices between bond and stock funds. Lastly, we compare the predictive power of our loss aversion measure against other traditional measures of risk taking, including loss aversion using the DEEP measure (Toubia et al 2013), subjective risk aversion, and a measure of risk aversion from the economics literature (Kapteyn & Teppa 2011). We find that our loss aversion measure has predictive value over and above what risk perception captures; specifically, it suggests that loss aversion measures aspects of risk-taking preference that are not completely captured by subjective beliefs about the level of risk in a financial gamble. Many policy makers and financial services firms currently employ generic risk perception questions when working with new clients; this new loss aversion measure offers them the ability to gather individual information that is more predictive of actual financial choices, including Social Security claiming decisions.

## **2. Development of Loss Aversion Measure**

A key psychological influence on claiming decisions that we have observed in previous studies is an individual's measure of loss aversion, due to the perspective that not claiming early may result in a loss of benefits relative to a breakeven calculation or relative to the individual's

own contributions into Social Security during their working years. Note that high levels of loss aversion have different implications than high levels of risk aversion, since individuals with high levels of risk aversion should be more, rather than less, likely to want to delay claiming. In other words, because Social Security provides a guaranteed stream of lifetime income, larger monthly benefits are seen as a way to reduce risk and should be most highly valued by individuals with significant levels of risk aversion. Loss aversion, on the other hand, leads to earlier claiming because concerns that prior contributions to Social Security will be “lost” or wasted if claiming is delayed can motivate individuals to claim as soon as possible and avoid that loss.

There are several implications of using loss aversion, rather than risk aversion, to explain claiming preferences. A very substantial behavioral literature exists on manipulations that moderate loss aversion in a wide variety of tasks. By thinking about the Social Security claiming decision in a loss aversion context, we can begin looking for ways to apply those findings to creating information interventions that influence the claiming decision. Since benefits may be perceived as already “owned” by the individual, the decision of when to claim begins to resemble an endowment effect situation, where currently held (owned) options are more highly valued than the same option when not owned. The standard explanation for the endowment effect is loss aversion, in which the owner sees giving up the option as a loss and therefore demands a higher compensation. If Social Security benefits are also perceived to be owned by a potential claimant, the decision to delay looks like a potential loss (relative to either the breakeven value and/or death before any benefits are received). Thus, individuals who are high in loss aversion should be less likely to be willing to delay claiming.

Given the importance of loss aversion in explaining claiming and other behaviors, several approaches for measuring it at the individual level have been developed. Most of the approaches

assume an underlying model of decisions under risk (Kahneman & Tversky, 1979), and use simple 50:50 two-outcome gambles. While sophisticated model-based estimation techniques have much to recommend them, we offer an alternative approach that is model-free and based on choices made between slightly more complex mixed three-outcome gambles. In particular, our loss aversion measure is based on ideas presented in Brooks and Zank (2005). They offer several reasons for adopting a more model free approach to measuring loss aversion, including the avoidance of 50:50 gambles; we also note that a choice between two options differing on two dimensions of value (gain versus loss) evokes more System 2 thinking (Kahneman, 2011). Many important “real-world” consumer decisions under risk involve more than simple two-outcome gambles.

To obtain a precise measure of individual differences in degrees of loss aversion we present participants with a series of gamble choices. Participants are asked at each step to choose between two mixed three-outcome gambles, A and B. Each gamble has one positive outcome at 45% chance, a zero outcome at 10% chance, and one negative outcome at 45% chance. We find, for example, that most respondents (often above 70%) express some degree of loss aversion by preferring a loss averse (LA) gamble (\$400, .45; \$0, .10; -\$400, .45) to a matched gain seeking (GS) gamble (\$600, .45; \$0, .10; -\$600, .45). Building on this base gamble, we go beyond prior literature and systematically change the amounts to be gained (or lost) for either A or B in each pair. A sample of some of these gambles is shown in Figure 1. The different pairs of gambles with different levels of gain vs. loss tradeoffs are presented to the respondents in random order. The ultimate result is that this series of simple paired comparison choices yields an overall measure of loss aversion per participant. Below, we report on the overall pattern of results that

comes from using this new measure, as well as its relationship to standard demographic variables.

Our studies on Social Security claiming described below do find that loss aversion, when measured at the individual level, is a significant predictor of preference for early versus late claiming. The empirical finding that individual level heterogeneity in loss aversion predicts claiming preferences supports theories proposed by other researchers on this topic. As noted by Brown (2007), individuals who delay claiming their Social Security benefits beyond age 62 are essentially purchasing an inflation-indexed annuity for the future; however, consumers sometimes view the purchase of an immediate annuity as “gambling on their lives.” Extending that idea, Hu and Scott (2007, p.8) suggest examining annuity choice from the perspective of more behavioral models such as Cumulative Prospect Theory (Tversky & Kahneman, 1992) under the argument that CPT is a better behavioral model than the classic expected utility model. Our findings support the argument that incorporating loss aversion into models of claiming decisions may improve those models predictive power.

### **3. Results for Individually Measured Loss Aversion**

#### *3.1 Overview of loss aversion measure studies*

The results presented here represent data collected in six different online studies conducted by the authors from 2012 through 2015. These studies were run using national panels provided by data collection firms Qualtrics and Survey Sampling International. The Qualtrics survey panels, while convenience samples, provide a distribution of American adults whose demographics fit reasonably well with national averages (see Table 1 for demographics from all

six studies). Participants are recruited and screened by the firms and are paid for their participation. During the studies, participants are further screened by relevant demographic variables (for example, by age) and according to their successful completion of an attention check (see Oppenheimer, Meyvis, and Davidenko 2009). We find results from these surveys that are similar to the well-known, and often studied, HRS data on key questions such as life expectations and savings for retirement.

The six studies differed in the types of displays for describing Social Security retirement benefits based on age of claiming. For example, in some studies, the benefits were shown as cumulative benefits for different live-to ages, while in other studies, only monthly benefit amounts were described. Also manipulated between studies were whether life expectations were asked in a live-to or die-by frame, whether life expectations were collected before or after the claiming decision, and whether questions about annuities were included. Among studies that used a cumulative payout table for benefits, we also manipulated the display by changing which live-to years were represented and whether they were arranged in rows vs columns. What is consistent across all studies is that the set of questions which constitute the loss aversion measure were asked at the end of the study, after any claiming or other retirement questions, but before collection of demographics (gender, health, etc.). It is this individual level loss aversion measure that we will focus on analyzing in this section; we will return to questions of claiming age decisions in the next section of the paper.

In all studies, at least nine, and usually eleven, loss aversion questions were asked. As described above each question takes the form of a choice between two gambles with the same probability distribution but different outcomes. A set of nine questions is consistent across all six studies, while combinations of four other questions are included in a subset of the studies. We

will analyze the loss aversion results for each study separately, and then look at the aggregated results for the nine loss aversion questions that were always asked in Studies 2 through 6.

Also of interest to us in this project is how individual differences in other variables affect these loss aversion measures. In all studies, we collect data from our study participants about gender, current age, life expectations, and savings. In some studies, we also collect information about subjective health, income, marital status, and intertemporal patience. We expect, based on prior literature, that there should be differences in reported loss aversion based on these demographic variables. For example, just as women are typically more risk averse in surveys, they are sometimes more loss averse, and we should expect to see that pattern here.

The methods and participants for each study are as follows:

*Study 1:* Study 1 is an online study with a convenience sample of U.S. residents aged 35 to 65 ( $N = 832$ ) who were recruited and run online through the internet panel company Survey Sampling International. Respondents (48.7% female,  $M_{age} = 50.5$ ) were paid a fixed amount for participation. Participants in the study were randomly assigned to one of four conditions in a 2X2 design (judgments of life expectation before or after dependent variables, crossed by life expectations collected in “live to” versus “die by” frame). There were four separate dependent variables, all of which capture whether the individual is being myopic about retirement income decisions. Specifically, we ask about hypothetical decisions regarding Social Security claiming age, preference for an immediate single life annuity, choice of equities versus risk-free bonds for retirement assets, and amount of income to allocate to retirement savings. We also collect substantial additional information about each participant to use as covariates in our analysis, including age, gender, current savings, perception of future social security solvency, life

expectancy, loss aversion, subjective health, and numeracy. Summary details for the participants in this study, and the other five studies, are provided in Table 1.

*Study 2:* Study 2 is an online study with a convenience sample of U.S. residents aged 30 to 60 (N = 1474) who were recruited and run online through the internet panel company Qualtrics. Participants (49.8% female, Mage = 44.3) were paid a fixed amount for participation. Participants in the study were randomly assigned to one of five conditions which tested the effects of benefit payout displays on Social Security claiming decisions. The displays provided information on benefits in either a purely monthly amount (condition 1) or in cumulative amounts at a variety of different ages displayed in a matrix format. Conditions further varied based on the conditional ages in the payout matrix (age 73 to age 93 versus age 63 to age 93) and on whether or not probability of living to each age, taken from the SSA website, was displayed. In addition to our main dependent variable of predicted claiming age, we collected a variety of demographic and psychographic measures to use as covariates and provide us with additional insight on participants' inputs to the claiming decision. For all participants, we collect self-reported age, gender, education, household income, retirement savings, numeracy, and health as demographics. As psychographics, we ask for perceptions of SSA solvency, perceptions of fairness, and loss aversion.

*Study 3:* Study 3 is an online study with a convenience sample of U.S. residents aged 40 to 65 (N = 1113) who were recruited and run online through the internet panel company Qualtrics. Participants (49.7% female, Mage = 53) were paid a fixed amount for participation. Participants in the study were randomly assigned to one of six conditions in a 3x2 design. The first design factor was a modification of the cumulative payout tables used in Study 2. Participants saw either basic information of monthly benefits with no cumulative information, a

cumulative payout table that started at age 62 and went to age 70, or a reversed cumulative payout table that had age 70 on the left and descended to age 62 on the right. The other design factor was a priming manipulation; half of participants, as part of the study introduction, were given information about the average amount of contributions a worker has made into the Social Security system at the point of retirement. In addition to these manipulations of cumulative payout information and the prior contribution prime, we collect our standard measures of self-reported age, gender, retirement assets, and health as demographics. As psychographics, we ask for perceptions of SSA solvency, perceptions of fairness, and loss aversion. We also introduce in this study a measure of intertemporal discounting - a set of three questions adapted from Schreiber and Weber (2013).

*Study 4:* Study 4 is an online study with a convenience sample of U.S. residents aged 40 to 62 (N = 1452) who were recruited and run online through the internet panel company Qualtrics. Respondents (69.7% female, Mage = 53) were paid a fixed amount for participation. Participants in the study were randomly assigned to one of eight conditions. The first manipulation is the order in which participants saw either an annuity or Social Security claiming task. The second manipulation was in the presentation of information about cumulative payouts for the annuity and for Social Security claiming, very similar to the manipulations in Studies 2 and 3. Specifically, participants either saw basic information regarding monthly income from either Social Security or the annuity, or they saw a table with cumulative payouts for the ages 70, 75, 80, 85, 90, and 95. Participants who saw the cumulative table for one task (e.g., the claiming task) also saw the cumulative table for the second task (e.g., annuities). A third manipulation was specific to the annuity task, in which the default option was described as either a lump sum payout (like a 401k) or an annuitized payout (like a pension).

In addition to our dependent variables for claiming age and annuity likelihood, we collected individual difference measures of life expectation (taken in a “live to” frame), loss aversion (based on an 11-item measure), intertemporal patience (a 4-item measure), and perceived ownership for either the SSA contributions or the annuity. Importantly, we ran multiple versions of our loss aversion measure in this study, manipulating whether the probabilities of the three outcomes per gamble were presented in a 45%-10%-45% format or in a 33%-33%-33% format. This allows us to test whether our loss aversion measure is sensitive to the outcome probabilities. Finally, we collect our standard other demographic information: age, gender, current savings, and perception of future social security solvency.

*Study 5:* Study 5 is an online study with a convenience sample of U.S. residents aged 40 and above ( $N = 1010$ ) who were recruited and run online through the internet panel company Qualtrics. Respondents (71.2% female,  $M_{age} = 57$ ) were paid a fixed amount for participation. Participants in the study were randomly assigned to one of four conditions in a 2X2 design, extremely similar to Study 4. The first manipulation is the order in which participants saw either an annuity or Social Security claiming task. The second manipulation was in the presentation of information about cumulative payouts for the annuity and for Social Security claiming. In addition to this 2X2 design, this study had three variations of the annuity task, resulting in a total of 12 conditions in the full design. The differences in the annuity task were in how the annuity decision was described, as either a purchase task, an annuity default to lump sum conversion task, or a lump sum default to annuity conversion task. We again collect individual difference measures of life expectation, loss aversion, intertemporal patience, and perceived ownership for either the SSA contributions or the retirement plan option (savings, annuity, or lump sum). We also collect substantial additional information about each participant to use as covariates in our

analysis, including age, gender, current savings, and perception of future social security solvency.

*Study 6:* Study 6 is an online study with a convenience sample of U.S. residents aged 40 to 65 (N = 831) who were recruited and run online through the internet panel company Qualtrics. All participants were required to pass multiple attention filters. Participants (49% female, aged 40 to 62) were paid a fixed amount for participation. Some 6.1% (n=51) subjects were excluded from further analysis due to violations of coherency for the life expectation task or invalid responses such as all 0% for all life expectation ages. N=780 were retained for further analysis.

Participants in the study were randomly assigned to one of four conditions in a 2x2 design. The first design factor was a modification of the cumulative payout tables used in the previous studies. Participants saw the cumulative payout information arranged either with representing claiming age options and columns representing the age for the cumulative payout figure, or a reversed table that put the claiming ages into columns and the payout ages into the rows. The second manipulation is whether the life expectation judgments were collected in a “live to” frame versus a “die by” frame. The dependent variables are again tasks about both predicted Social Security claiming age and likelihood of purchasing an annuity. Unlike Studies 4 and 5, the order of tasks was held constant with the claiming task always completed first and the annuity task second, and there was only one version of the annuity task. In addition to the manipulations of cumulative payout information and the life expectation frame, we collect our standard measures of self-reported age, gender, and retirement assets as demographics. As psychographics, we ask for perceptions of SSA solvency, perceived ownership, intertemporal patience, and loss aversion.

In all six studies, data was screened to make sure that participant responses were reasonable within certain limits. For example, life expectations were not allowed to exceed 120 years old. Individuals who failed the attention filter or who gave nonlinear answers for life expectation probabilities were excluded from the sample. Also excluded were any participants who exhibited more than two violations of stochastic dominance in their choices among the loss aversion gambles.

The rest of this section will proceed as follows. First we present the summary results for the loss aversion measure for each of our six studies separately. Then we present the aggregated results for Studies 2 through 6, where the loss aversion questions were consistent. We compare these results to previous findings in the loss aversion literature to ensure that our overall pattern of results is consistent with that prior work. Next we check whether minor variations in how the loss aversion gambles are presented – specifically, whether the gamble probabilities are in the form of 45%-10%-45% versus the form of 33%-33%-33% - affects the overall loss aversion results. Finally, we analyze how the loss aversion measure relates to our demographic measures and other psychological measures such as intertemporal patience.

### *3.2 Per study summary and aggregated results of loss aversion measure*

As noted in Section 2, the loss aversion measure tested in these studies was refined over the course of data collection. Gamble pairs that represented low levels of loss aversion were removed, since there were few respondents at that end of the scale, and gambles to capture very high levels (above  $\lambda=2.5$ ) were added to reduce crowding in the high end of the distribution. To account for the changes in the measure as the studies proceed, we begin by showing the results of each study separately. We then move to an aggregated analysis, using only

the set of nine gambles that are consistent across Studies 2 through 6. Furthermore, we present these results in two separate but complementary formats. First we present them as raw scores, where the choice of the loss averse gamble within each pair is treated as a “point” which are then summed up for a total score. This “raw score” measure will be higher for individuals who choose the loss averse gamble more often. Note that individuals who are inconsistent more than once between their choices (i.e., violate stochastic dominance in their responses) have been removed from the dataset, so that the mapping between raw score and true loss aversion is consistent. The second presentation format translates these raw scores into a loss aversion coefficient (traditionally called lambda,  $\lambda$ ) which reflects the size of the gain that a participant requires to be willing to incur a large loss. While the exact mapping between raw score and lambda is different between studies since the underlying gambles are changing, once the translation of lambdas is made per study, the resulting distributions can be more easily compared across the studies.

Starting with the distribution of raw scores (i.e., the number of loss averse choices selected) per participant, we see that the loss aversion measure follows a relatively normal distribution in most of our studies (see Figure 2). The distribution is more skewed at the high end of the measure in Study 1, where we experience a ceiling effect on the high end based on the set of gambles that were offered to participants. In Studies 2-6, we expand this end of the distribution, and as a result see a more normal distribution. Figure 3 provides a distribution with data aggregated across Studies 2-6, where we have a common set of nine gambles that were presented in all studies. This figure also shows how the distribution varies by gender; by observation, we see that women tend to have higher loss aversion measures than men. We will analyze this effect of gender in more detail below.

As noted above, we also wanted to explore how these measures map to lambda ( $\lambda$ ), the measure of loss aversion used in much of the previous literature. The next set of figures takes the same data but translates the raw scores into the corresponding loss aversion coefficient based on the ratio of gamble outcomes. Since several of the gambles within each study may translate to the same lambda, there are fewer bars in each histogram. Again, Figure 4 provides a histogram for each of our studies. One thing to immediately note is that there is a sudden increase from lambdas below one (which may be thought of as loss-seeking) to lambdas of one and above (loss averse). We also provide a histogram for the combined data from Studies 2-6 in Figure 5, again broken out by gender. This pattern of results for the loss aversion coefficient is consistent with findings from prior measures of loss aversion using more complex measurement tools (e.g., Toubia et al 2013), but with a more efficient and easier to administer experimental design.

### *3.3 Manipulations of outcome probabilities*

In Study 4, we ran a variation of our loss aversion measure in which the outcome probabilities associated with the gambles was manipulated. Specifically, while all other studies used outcome probabilities of 45%-10%-45%, this study ran variations of the loss aversion questions where the probabilities were 33%-33%-33%. Thus, while a typical gamble in the prior format may offer a set of outcomes that were described as a 45% chance at winning \$700, a 10% chance at \$0, and a 45% chance at losing \$600, the same gamble in this manipulation would be described as a 33% chance at winning \$700, a 33% chance at \$0, and a 33% chance at losing \$600. Note that this change in the probabilities directly affects the expected value of the gamble in a normative framework, moving it from \$45 to \$33. Within a Prospect Theory framework, the effect of the change in probabilities have less of an effect on the subjective value since the

probability weighting function is relatively flat in the region between 33% and 45%, yielding a subjective probability that is relatively unchanged. We therefore predict that changing the probabilities of the outcomes in this way will have little to no effect on the loss aversion measures that we collect from our participants.

To test this hypothesis, the 1452 participants of Study 4 saw the loss aversion gambles in one of the two formats. We then test whether this change affects the average loss aversion measure for both groups. A two-sample Wilcoxon rank-sum (Mann-Whitney) test finds that the probability condition does not have a significant effect on the loss aversion measure ( $z=-1.614$ ,  $p=.11$ ). Thus, as expected, it is the size of the relative gains and losses in the gambles that more strongly affects choices, rather than the probabilities of those outcomes. Figure 6 shows the difference in the raw loss aversion measure distribution for the two formats.

### *3.4 Relationship of individual loss aversion to other measures*

An important goal of this data collection was to understand how the individual loss aversion measure changes according to the heterogeneity of the population being measured. By collecting a standard set of demographic and other psychographic measures across our studies, we are able to investigate this question in detail. Note that we will also be exploring how our individual loss aversion measure correlates with other related measures (including standard economic risk aversion) in the Section 4 of this manuscript.

The major demographic measures that we can relate loss aversion to are gender, current participant age, subjective life expectation, subjective health, savings, household income, marital status, military status, and numeracy. We also have two psychographic measures of interest: intertemporal patience, and belief that Social Security benefits will exist in the future (SSA

solvency). Note that not all measures are collected in all studies; for example, marital and military status are only measured in Study 6, numeracy is only measured in Study 2, and subjective health is not measured in Studies 4-6. To begin exploring these relationships, Table 2 provides a correlation table showing the correlation between the measures that exist in all six studies: current age, life expectation, gender, savings, and SSA solvency. Many of these measures are significantly correlated with each other; the strongest correlation is between SSA solvency and current age ( $r=.41$ ,  $p<.001$ ).

Moving to the analysis of how loss aversion is affected by each measure, we start with the effect of current age on loss aversion. Using a both chi-squared tests and ANOVA, with raw age or standardized age, we find no significant effect of age on loss aversion (for the ANOVA,  $p=.51$  for raw age, and  $p=.18$  for standardized age). There is, however, a significant relationship between loss aversion and expected age (average life expectancy). Expected age has a significant negative correlation with loss aversion, such that as a respondent's life expectancy increases, the loss aversion measure decreases (in an ANOVA,  $p<.001$  for both raw expected age and standardized expected age). Whether it is that individuals with longer life expectancy are less loss averse, or that individuals that are not loss averse are more optimistic about their life expectancy, we cannot say.

Subjective health per participant was measured in Studies 2 and 3, and chi-squared tests of the relationship between this 7-item measure and our loss aversion measure find that they are significantly related ( $p=.03$ ). Individuals with higher subjective health tend to have lower loss aversion. For example, the average loss aversion score for individuals who rate themselves low on subjective health (a 1 on the 7-point scale) is 5.31, while the average loss aversion score for

individuals who rate themselves highest on the scale (a 7) is 4.51. Again, we cannot determine causality in this relationship, only the significance of the correlation.

Self-reported savings was measured in all of our studies and we can test its relationship to loss aversion as well. We may expect that more loss averse individuals will save less, since giving up current income feels like a loss (Thaler & Benartzi 2004). We do see a marginally significant effect in this direction; there is a negative correlation between loss aversion and reported savings, such that as savings increases, loss aversion decreases. A Kruskal Wallis chi-squared test shows a significant effect at  $p=.05$ , while a one-way ANOVA indicates an effect at  $p=.08$ .

Many of our remaining demographic measures were only collected in a subset of our six studies. Self-reported household income was measured in studies 2 and 6, and a chi-squared test shows no significant correlation between income and loss aversion ( $p=.59$ ). Marital status and military status were both collected in Study 6. Tests indicate that marital status is not significantly correlated with loss aversion (chi-squared  $p=.73$ ), and military status is only marginally significantly correlated with loss aversion (chi-squared  $p=.06$ ) such that as individuals increase in military involvement, their loss aversion also increases. Finally, numeracy, a measure of numerical thinking that is also correlated with intelligence, was collected in Study 2. We find that numeracy is not significantly correlated with loss aversion ( $p=.23$ ).

Our last two individual measures were more psychological in nature. One is a measure of intertemporal patience, collected on a 4-point scale. The second is the subjective belief in whether Social Security benefits will continue to be available in the future, a judgment of SSA solvency. Using intertemporal choice as a categorical measure based on the small number of

scale values, a Kruskal-Wallis chi-squared test finds a significant correlation between intertemporal choice and loss aversion ( $p=.0001$ ). Individuals with higher impatience (a 0 on the measure) are more loss aversion (average score of 5.41) than individuals with more patience (a 3 on the measure, average loss aversion of 4.92). Since both loss aversion and intertemporal patience at the individual level are predictive of Social Security claiming decisions, this suggest that these individuals who are both forward looking and not as concerned about losses will be more likely to agree to delay their benefits. Finally, when individuals are asked to judge the solvency of the SSA retirement benefits system, we find that there is no significant relationship between SSA solvency beliefs and loss aversion ( $\rho=-.009$ ,  $p=.48$ ).

While these individual tests of significant correlation are insightful, putting the set of measures available across the majority of the studies into a regression analysis allows us to control for the high correlations between some of the measures as shown in Table 2. We thus run a series of regressions, shown in Table 3, with loss aversion as the dependent variable and current age, expected age, gender, savings, SSA solvency, intertemporal patience, and health as independent variables. The first regression model uses Studies 2 through 6 ( $N=5,863$ ), and thus leaves out intertemporal patience and subjective health since they were not included in all studies. We find that expected age and gender are the largest and most significant effects on loss aversion, at  $\beta=-.14$  and  $\beta=-.43$  respectively. Individuals who expect to live longer and who are male have lower loss aversion scores than their counterparts. In the second model in the table, we bring in intertemporal patience from Studies 3 through 6 ( $N=4,305$ ). Expected age and gender continue to be significant and largely unchanged, and now intertemporal patience is also now significant. Finally, the last model includes subjective health and represents Study 3 ( $N=1,016$ );

here, intertemporal patience becomes insignificant, but expected age and gender continue to be strong predictors of individual loss aversion.

#### **4. Loss Aversion as a Predictor for Claiming (and other) Behaviors**

##### *4.1 Study 1: Loss aversion as a predictor of claiming and annuities*

Study 1 was somewhat unique among our set of six studies in that it included a wider set of dependent variables. Specifically, we included measures of not just Social Security claiming, but other types of forward-looking financial decisions such as whether or not to save for retirement, whether to invest in equities versus bonds, whether to select an annuity, and what age to claim retirement benefits. We analyze this study separately from the other five studies in order to see how the loss aversion measure affects each of these retirement behavior measures.

We begin with an analysis of the Social Security claiming measure. Individuals were asked when they expected to begin claiming benefits and could choose any age from 62 to 70 years old. A regression of claiming age on the full set of demographic and psychographic measures, as well as indicators for the order and framing conditions, finds significant effects of self-reported health, life expectancy, perceived SSA solvency, and framing (live-to versus die-by). All effects are reported in Table 4. Interpretation of these results indicates that individuals are more likely to claim at an older age if they are more subjectively healthy, if they expect to live longer, and if they think Social Security benefits will still exist when they retire. Looking more closely at the effects of life expectation on claiming, people who preferred to claim at ages

65 or earlier expressed probabilities of living to ages 75 and 85, on average, of .60 and .41, respectively. In contrast, people who preferred to claim at ages 67 or later had probabilities of living to ages 75 and 85, on average, of .68 and .50, respectively.

The effects of framing and order manipulations are mixed. Order does not have an effect; thinking about life expectancy before or after answering the claiming question does not significantly change responses. However, framing does have an effect, but in a surprising way. A close investigation of the framing effect shows that there is no main effect of framing ( $\beta = -.09$ ,  $p = .37$ ) unless an interaction between frame and expected age is included in the model. At this point, the effect of framing becomes negative and the interaction positive. Separate analyses of the two frames allows us to understand this interaction more clearly, and shows that the effects of higher life expectancy are only significant when individuals are in the live-to frame ( $\beta = .05$ ,  $p < .001$ ). When individuals are in the die-by frame, effects of higher life expectancy are not significant ( $\beta = .01$ ,  $p = .44$ ) but the regression constant is higher (65.9 vs 62.2), indicating that these participants are reporting later intended claiming but not accounting for differences in life expectancy when doing so.

Continuing with the other dependent variables of annuity preference, choice of equities, and income allocated to savings, we find similar results. The annuity preference measure represents an individual's self-reported likelihood of purchasing a standard life annuity in retirement as collected on a percentage scale with increments of 10 (0%, 10%, etc. up to 100%); higher numbers represent more interest in an annuity. The choice of equities was asked as what percentage of retirement savings the individual would prefer to invest in bonds rather than stocks and was collected on a continuous scale of 0-100; here, higher numbers indicate stronger preference for bonds. Finally, the savings allocation measure was taken as the answer to a

question about what percentage of one's paycheck participants would like to save toward retirement, with answers ranging from 1% to 20%. Regression results are again shown in Table 4. For annuities, younger individuals, those with longer reported life expectancy, and those worried about SSA solvency report more interest in annuities, and again framing and life expectancy interact in a pattern similar to the one observed for claiming. Framing does not have these effects on the bond and savings questions, but we do see significant effects of loss aversion, with more loss averse individuals strongly preferring bonds and less likely to save for retirement.

One final regression combines the four dependent variables into a single behavioral score that indicates overall myopia in retirement decisions. The desire to claim Social Security benefits early, a dislike of life annuities, a preference for bonds over equities, and a disinclination to save for retirement can all be interpreted as representing a short-term perspective regarding retirement income. To combine the four decisions into a single measure, we adjust each measure into a standardized z-score with higher values representing more long-term perspective (the measure of preference for bonds was accordingly reverse-coded). Echoing results from the earlier separate models, we see that higher subjective health, longer life expectancy, lower loss aversion, and higher predicted SSA solvency all contribute to a more forward-looking perspective in retirement decisions. The effect of framing is again significant, but only when the interaction between frame and expected age is retained, suggesting that individuals in the live-to frame are reacting (appropriately) to their own predicted life expectancies, but those in the die-by frame are not.

Our main findings in this study show that individual measures of both loss aversion and life expectancy are important predictors of individuals' retirement decisions. Specifically, longer predicted life expectancy predicts less myopic behavior, with individuals choosing to delay

Social Security claiming, expressing a preference for life annuities, choosing equities, and saving a higher percentage of their income for retirement. Higher levels of loss aversion have the opposite effect. Importantly, loss aversion and life expectancy are not correlated, showing that they are independent influences. Many demographics, such as age and gender, have little to no effect outside of their influence on predicted life expectancy; the only exception is subjective health, which has an effect in some models. Perceptions of SSA solvency are also important inputs into these decisions.

#### *4.2 Studies 2-6: Loss aversion as a predictor of SSA claiming intentions*

We have seen in Study 1 that the loss aversion measure is predictive of several retirement related decisions. Our next analysis focuses only on the Social Security benefits claiming decision, and looks at whether our loss aversion measure is predictive of this decision. A dependent variable for predicted Social Security claiming age was included in each of Studies 2 through 6. In all cases, participants were asked when they expected to claim Social Security, with choices of age 62, 64, 66, 68, or 70, or an option of “I don’t know”. While each of these studies manipulates the provision of cumulative payout information and/or the life expectation question frames, we focus here only on how the individual difference variables affect the claiming decision. As noted before, in each of these studies we collect our standard measures of self-reported age, gender, and retirement savings as demographics. As psychographics, we ask for perceptions of SSA solvency, perceived ownership, intertemporal patience, and loss aversion (our primary independent variable of interest in this analysis).

Results of a series of linear regressions with claiming age as the DV are shown in Table 5. Not surprisingly, we find significant effects of many of our individual difference variables, consistent with our findings in Study 1 and in prior research. Specifically, a longer expected age, lower perceived ownership of Social Security contributions, lower loss aversion, and more intertemporal patience are all indicators of a later claiming age across all of the studies. Women and younger subjects also indicate that they will claim later, although the gender effect is not consistently significant. Concerns about Social Security program solvency are also generally significant although the effect size is relatively small (.01 or below).

Other than Study 2, the impact of loss aversion is significant and of a consistent effect size across the studies. In the aggregated data analysis in the last column of Table 5, we see that the coefficient on the loss aversion score is -.074. The interpretation of this is that an individual with high loss aversion will claim sooner than one with low loss aversion. To take a more tangible example, consider two individuals with respective loss aversion scores of 3 and 9 on our scales. The individual with the lower loss aversion (equivalent to  $\lambda=1$ ) will claim at age 66.8, while the one with higher loss aversion (equivalent to  $\lambda=5$ ) will claim at 66.3, a difference of approximately 6 months (all else held equal).

#### *4.3 Loss aversion relationship to alternate measures*

As a final step, in a study not reported in detail here, we have tested the predictive power of our loss aversion measure against other traditional measures of risk taking. In an online study with 99 participants, we tested risk likelihood and risk perception for a series of gambles under different choice brackets (narrow, broad) and gamble types (positive EV mixed, negative EV

mixed, and strictly negative). We then collected individual measures of loss aversion via our nine-point scale, loss aversion using the DEEP measure (Toubia et al 2013), subjective risk aversion, and a measure of risk aversion from the economics literature (Kapteyn & Teppa 2011). As shown in Table 6, we find that our loss aversion measure is significantly positively correlated with the DEEP loss aversion measure ( $r=.35$ ,  $p<.05$ ). On the other hand, it is not significantly correlated with either subjective risk aversion ( $r=-.04$ ) or economic risk aversion ( $r=-.20$ ) measures, suggesting that loss aversion is capturing a different construct from risk aversion. Importantly, our loss aversion measure has a significant negative effect on choosing to gamble ( $B = -0.07$ ,  $p = 0.03$ ) across all gamble choices, even after controlling for risk perception (the greatest predictor of risk-taking in the extant literature). This finding suggests that our loss aversion measure has predictive value over and above what risk perception captures; specifically, it suggests that loss aversion measures aspects of risk-taking preference that are not completely captured by subjective beliefs about the level of risk in a financial gamble. Many financial services firms and policy makers currently employ generic risk perception questions when working with new clients; this new loss aversion measure offers them the ability to gather individual information that is more predictive of actual financial choices.

## **5. Summary**

Overall, this paper provide a brief outline of the development of a new, highly efficient, loss aversion measure that can be easily used in short survey contexts. Unlike earlier, more complex measures, this measure allows us to quickly capture individual-level loss aversion, which can then be used to predict individuals' behavior and choices in a variety of retirement

related decisions. We began by analyzing the loss aversion measure itself, and found that not only is it internally consistent across multiple studies with a large sample of participants, it also reflects demographic differences in sensible ways. We also tested whether the measure was sensitive to the probability distribution of the outcomes within the gamble choices it utilizes, and found that the results are robust across these different formats. Finally, we have documented that these individual-level loss aversion measures are predictive for retirement decisions, especially the decision of when to claim Social Security benefits. These findings both replicate our prior research on this topic and provide strong support to hypothesized effects of how behavioral science and decision making literature can inform research on Social Security claiming (Knoll 2011). They also speak to the importance of including psychological measures in studies of how individuals choose to manage longevity risk, a problem that both Social Security benefits and annuities are designed to help solve.

While not analyzed in detail within this manuscript, the studies described here have also allowed us to test interventions that may affect Social Security claiming decisions. Note that our information-based interventions differ from the behavioral interventions that have been previously tested in the Social Security claiming area which have focused on manipulations of gain/loss framing (e.g., Brown, Kapteyn, and Mitchell 2011; Liebman and Luttmer 2009). We had found indications in prior testing that providing individuals with cumulative payout tables had contrasting effects for claiming decisions versus annuity decisions; the cumulative payout table increased preference for annuities (as in Shu et al 2015) but led to earlier claiming for Social Security. Thus, contrary to what has been suggested in the literature (e.g., Kunreuther et al 2013), the provision of information on the long term value of delaying claiming does not increase the likelihood that respondents will prefer to delay claiming. This suggests that claiming

later and purchasing an annuity may be less equivalent ways to manage longevity risk than has been suggested in the annuity literature.

More importantly, this rich dataset allows us to continue testing the interaction between individual difference measures like loss aversion with a variety of information interventions. We hope, in our ongoing work, to continue exploring this interplay between individual-level heterogeneity and intervention approaches through further analysis of possible interactions between these variables to understand whether specific interventions have larger or smaller effects on particular psychological sub-populations of respondents. For example, individuals with high levels of loss aversion may be more affected by information displays that highlight breakeven ages or cumulative payout amounts than those with low loss aversion. We are continuing to design new experiments which will collect individual difference measures (including loss aversion) and then present individuals with an intervention matched to their preferences and decision processing needs. Thus, our focus is on interventions that affect individuals' decision-making processes, rather than simply "nudge" them toward certain outcomes through information changes. By focusing on process, these interventions can better account for individuals' actual needs and tradeoffs, such as balancing liquidity concerns against mortality risks, as well as accounting for both emotional and rational reasons for claiming at different ages.

## References

- Brooks, P., & Zank, H. 2005. "Loss averse behavior." *Journal of Risk and Uncertainty*, 31(3), 301-325.
- Brown, J. R. 2007. "Rational and behavioral perspectives on the role of annuities in retirement planning." NBER Working Paper No. 13537.
- Brown, J.R., A. Kapteyn, O.S. Mitchell. 2011. "Framing effects and expected social security claiming behavior." NBER Working Paper 17018.
- Hu, W.Y., & Scott, J.S. 2007. Behavioral obstacles to the annuity market. *Financial Analysts Journal*, 63(6), 71-82.
- Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan.
- Kahneman, D., & Tversky, A. 1979. "Prospect theory: An analysis of decision under risk." *Econometrica: Journal of the Econometric Society*, 263-291.
- Kapteyn, Arie and Federica Teppa. 2011. "Subjective measures of risk aversion, fixed costs, and portfolio choice." *Journal of Economic Psychology*, 32(4), 564-580.
- Knoll, M.A.Z. 2011. Behavioral and Psychological Aspects of the Retirement Decision. *Social Security Bulletin*, 71(4), 15-32.
- Kunreuther, H. C., Pauly, M. V., & McMorrow, S. (2013). *Insurance and behavioral economics: Improving decisions in the most misunderstood industry*. Cambridge University Press. New York, NY.
- Leibman, J. B., E. F.P. Luttmer. 2009. The Perception of Social Security Incentives for Labor Supply and Retirement: The Median Voter Knows More than You'd Think. NBER Working Paper NB08-01.
- Oppenheimer, D. M., T. Meyvis, N. Davidenko. 2009. Instructional Manipulation Checks: Detecting Satisficing to Increase Statistical Power. *Journal of Experimental Social Psychology*, 45 (4), 867-72.
- Payne, John, Namika Sagara, Suzanne B. Shu, Kirsten Appelt, and Eric Johnson. 2013. "Life Expectation: A Constructed Belief? Evidence of a Live To or Die By Framing Effect," *Journal of Risk and Uncertainty*, 46, 27-50.
- Schreiber, Philipp and Weber, Martin. 2013. "Time Inconsistent Preferences and the Annuitization Decision." SSRN working paper.
- Shu, Suzanne B., Robert Zeithammer, and John Payne. 2015. "Consumer Valuation of Annuities: Beyond NPV," *Journal of Marketing Research*, forthcoming.

- Thaler, R., and Shlomo Benartzi, S. 2004. "Save More Tomorrow: Using Behavioral Economics to Increase Employee Saving." *Journal of Political Economy*, 112 (S1), S164-S187.
- Toubia, O., Johnson, E., Evgeniou, T., & Delquié, P. 2013. "Dynamic experiments for estimating preferences: An adaptive method of eliciting time and risk parameters." *Management Science*, 59(3), 613-640.
- Tversky, A. & Kahneman, D. 1992. "Advances in prospect theory: Cumulative representation of uncertainty." *Journal of Risk and Uncertainty*, 5(4), 297-323.

**Table 1: Participant demographics from Studies 1-6**

	<b>Study 1 (n=832)</b>	<b>Study 2 (n=1432)</b>	<b>Study 3 (n=1113)</b>
Source		Qualtrics	Qualtrics
Age	min 35, max 65, mean 50.5	min 30, max 60, mean 44.3	min 40, max 65, mean 53
Gender	48.7% female , 51.3% male	49.8% female, 50.2% male	49.7% female , 50.3% male
Numeracy	min 0, max 8, mean 3.84	min 0, max 8, mean 3.30	n.a.
Health	min 1, max 7, mean 5.12	min 1, max 7, mean 4.98	min 1, max 7, mean 5.34
Retirement savings	min 2.5k, max 1.5m, median 12.5k	min 2.5k, max 875k, median 12.5k	
Subjective life exp.	min 47, max 130, mean 80.8	min 46, max 130, mean 85.7	min 48.6, max 120, mean 85.7
Loss aversion	min 0, max 9, mean 6.27	min 0, max 9, mean 4.58	min 0, max 9, mean 5.06

	<b>Study 4 (n=1452)</b>	<b>Study 5 (n=1010)</b>	<b>Study 6 (n=831)</b>
Source	Qualtrics	Qualtrics	Qualtrics
Age	min 40, max 62, mean 53	min 40, max 88, mean 57	min 40, max 62, mean 50
Gender	69.7% female , 30.3% male	71.2% female , 28.8% male	49.1% female , 50.9% male
Retirement savings	min 2.5k, max 1.5m	min 2.5k, max 1.5m, median 37.5k	min 2.5k, max 1.5m, median 12.5k
Subjective life exp.	min 52, max 120, mean 84.7	min 47, max 120, mean 86	min 48.3, max 120, mean 79.5
Loss aversion	min 0, max 10, mean 5.12	min 0, max 10, mean 5.71	min 0, max 10, mean 5.45
Intertemporal patience	min 0, max 3, mean 1.62	min 0, max 4, mean 2.14	min 0, max 4, mean 1.94

**Table 2: Correlation table for demographics measures****Correlation Table for Individual-Level Measurements**

	Age	Expected Age	Gender	Savings	SSA Exist
Age	-				
Expected Age	0.10***	-			
Gender	-0.07***	-0.13***	-		
Savings	0.16***	0.09***	0.003	-	
SSA Exist	0.41***	0.13***	0.05***	0.15***	-

**Table 3: Regression results for loss aversion demographic predictors**

Ordered Logistic Regression of Loss Aversion Measure on Individual-Level Variables				
	Loss Aversion	Loss Aversion	Loss Aversion	
	(1)	(2)	(3)	
Std Age	0.04+	0.003	-0.05	
	(0.02)	(0.03)	(0.10)	
Std Expected Age	-0.14***	-0.10***	-0.21**	
	(0.02)	(0.03)	(0.07)	
Gender	-0.43***	-0.38***	-0.53***	
(0 = Female, 1 = Male)	(0.05)	(0.06)	(0.11)	
Savings	-0.01	-0.01	-0.01	
	(0.01)	(0.01)	(0.01)	
SSA Exist	-0.0004	-0.001	-0.001	
	(0.001)	(0.001)	(0.003)	
Intertemporal Choice		-0.11***	-0.08	
		(0.03)	(0.07)	
Health			-0.04	
			(0.05)	
N	5,863	4,305	1,016	

Notes: (1) Model (1) is for the individual-level variables measured across all studies (2-6); Model (2) is for variables found in Studies 3-6; and Model (3) is for variables found in Studies 2 and 3. (2) Robust standard errors are reported in parentheses below the coefficient.

+  $p < 0.10$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

**Table 4: Regression results for Study 1**

	DV: claiming	DV: annuities	DV: bonds	DV: save	DV: combined
Constant	64.19*** (.99)	30.55*** (10.5)	41.64*** (9.0)	6.45*** (1.87)	-.52*** (.20)
<b><i>Demographics</i></b>					
Age	-.013 (.014)	-.30** (.15)	.072 (.13)	.04 (.03)	-.001 (.002)
Gender (female=1)	.083 (.104)	1.59 (1.1)	1.22 (.95)	.007 (.2)	.019 (.02)
Health	.173** (.08)	1.31 (.82)	.13 (.70)	.026 (.15)	.039** (.016)
Savings	0 (0)	.001 (.002)	.003 (.002)	.001 (0)	0 (0)
Numeracy	.065 (.06)	-.271 (.59)	-.53 (.51)	.266*** (.10)	.01 (.01)
Life expectancy	.031*** (.008)	.20** (.09)	-.173** (.08)	.027 (.02)	.008*** (.001)
Loss aversion	-.064 (.04)	-.678 (.46)	.847** (.39)	-.19** (.08)	-.025*** (.009)
SSA solvency	.012*** (.003)	-.082** (.04)	-.116*** (.03)	-.001 (.007)	.001** (0)
<b><i>Manipulations</i></b>					
Framing	-1.65*** (.66)	-13.62** (6.96)	-6.38 (6.14)	.037 (1.26)	-.35*** (.14)
Order	.117 (.098)	1.84* (1.04)	1.21 (.89)	-.127 (.18)	.01 (.02)
Framing * life exp	.02** (.008)	.20** (.09)	.09 (.08)	-.001 (.02)	.004*** (.001)

*Notes:* Reports non-standardized coefficients from OLS regressions. Standard errors are in parentheses.

\*\*\* Significant at the 1 percent level

\*\* Significant at the 5 percent level

\* Significant at the 10 percent level

**Table 5: Regression results for Studies 2-6, separate and aggregated**

	DV: S2 claiming	DV: S3 claiming	DV: S4 claiming	DV: S5 claiming	DV: S6 claiming	DV: all claiming
Constant	63.48*** (.646)	64.17*** (1.08)	65.51*** (.906)	66.88*** (.919)	67.91*** (.765)	66.99*** (.296)
Age	-.02*** (.007)	-.034*** (.014)	-.047*** (.013)	-.035*** (.011)	-.06*** (.016)	-.007** (.004)
Gender	-.107 (.129)	.076 (.169)	-.040 (.158)	.104 (.196)	-.431** (.183)	-.221*** (.072)
Life expectancy	.053*** (.005)	.062*** (.007)	.059*** (.006)	.040*** (.007)	.001 (.002)	.019*** (.002)
Loss aversion	-.038 * (.021)	-.067** (.028)	-.076*** (.026)	-.076*** (.03)	-.066** (.034)	-.074*** (.012)
Perceived ownership	-.064*** (.019)	-.083*** (.026)	-.122*** (.021)	-.140*** (.028)	-.068*** (.027)	-.107*** (.011)
Intertemporal patience		.346*** (.091)	.325*** (.076)	.457*** (.088)	.54*** (.094)	
SSA solvency	-.004** (.002)	-.008** (.003)	-.007*** (.003)	-.010*** (.003)	.0005 (.003)	-.006*** (.001)
N	1768	993	1394	955	820	6023

*Notes:* Reports non-standardized coefficients from OLS regressions. Standard errors are in parentheses.

- \*\*\* Significant at the 1 percent level
- \*\* Significant at the 5 percent level
- \* Significant at the 10 percent level

**Table 6: Correlations with other loss and risk measures**

Correlations Across Individual-Level Variables with non-SD LA (JP) only					
	Loss Aversion (JP)	Loss Aversion (DEEP)	Subj RA	Econ RA	Age
Loss Aversion (JP)	-	<b>0.35</b>	-0.04	-0.20	0.09
Loss Aversion (DEEP)	<b>0.35</b>	-	<b>-0.21</b>	<b>-0.15</b>	<b>0.10</b>
Subj RA	-0.04	<b>-0.21</b>	-	<b>-0.17</b>	<b>-0.21</b>
Econ RA	-0.20	<b>-0.15</b>	<b>-0.17</b>	-	-0.003
Age	0.09	<b>0.10</b>	<b>-0.21</b>	-0.003	-

Values in bold are significant at the  $p < 0.05$  level.

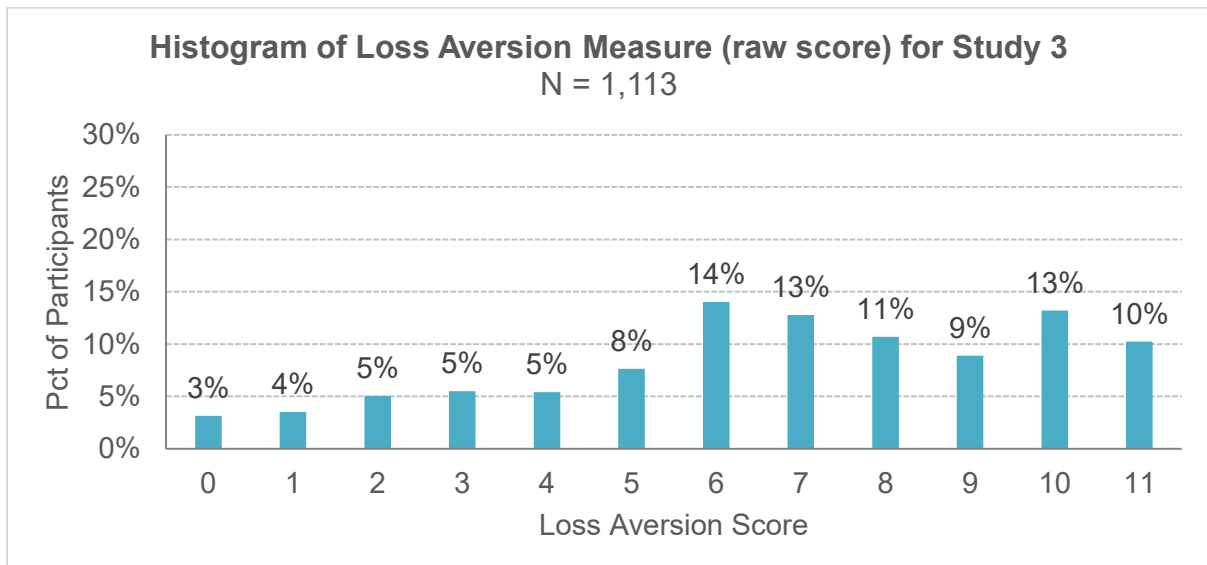
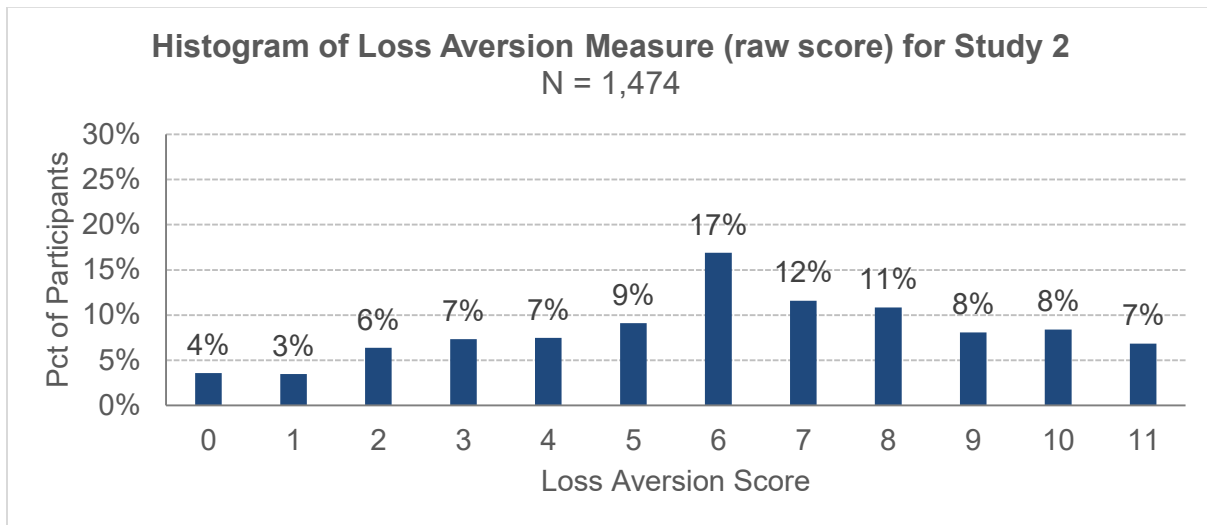
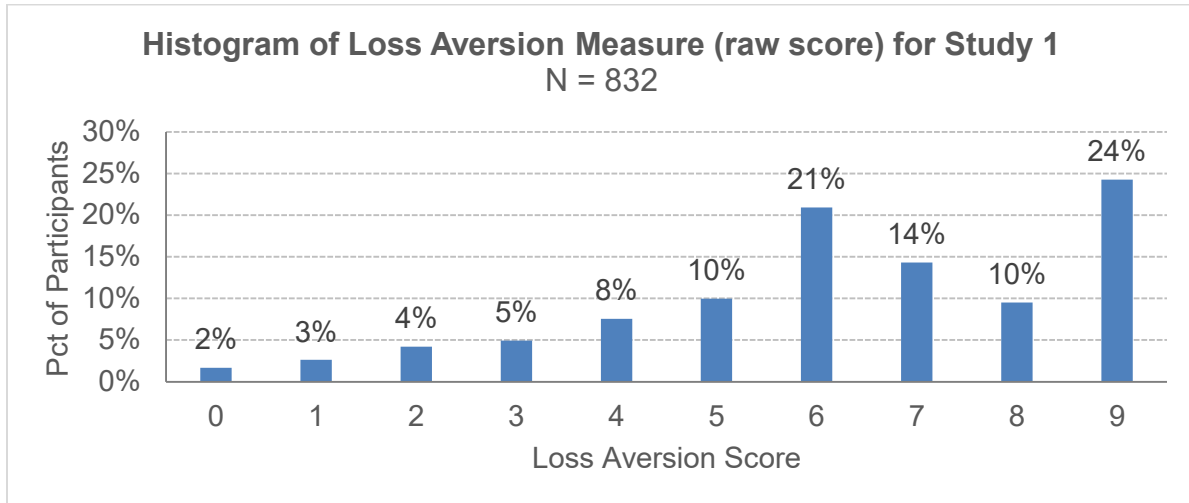
**Figure 1: Sample loss aversion gambles**

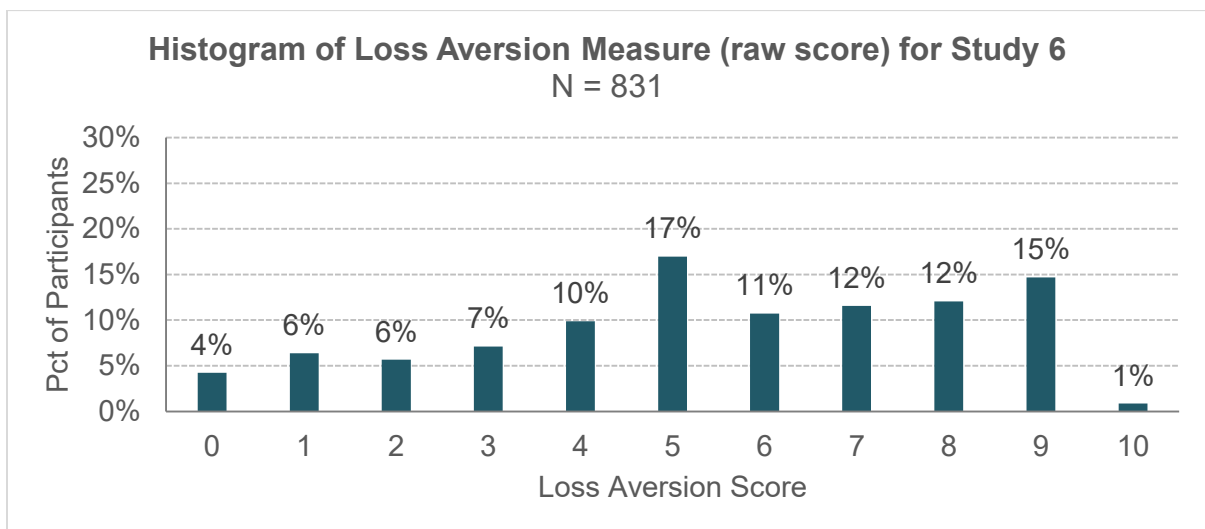
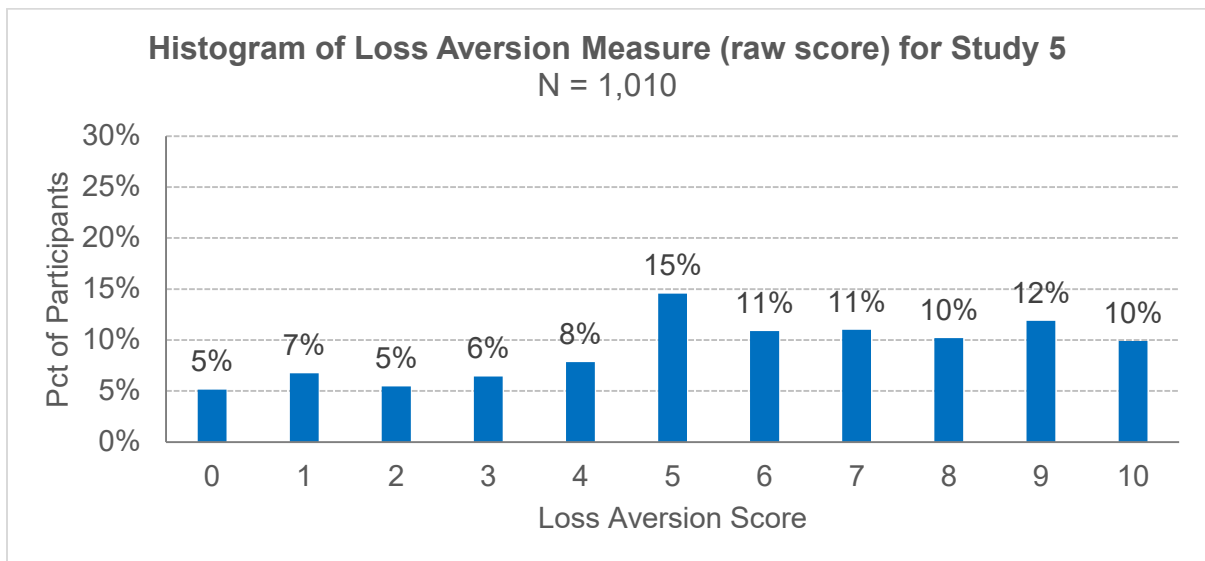
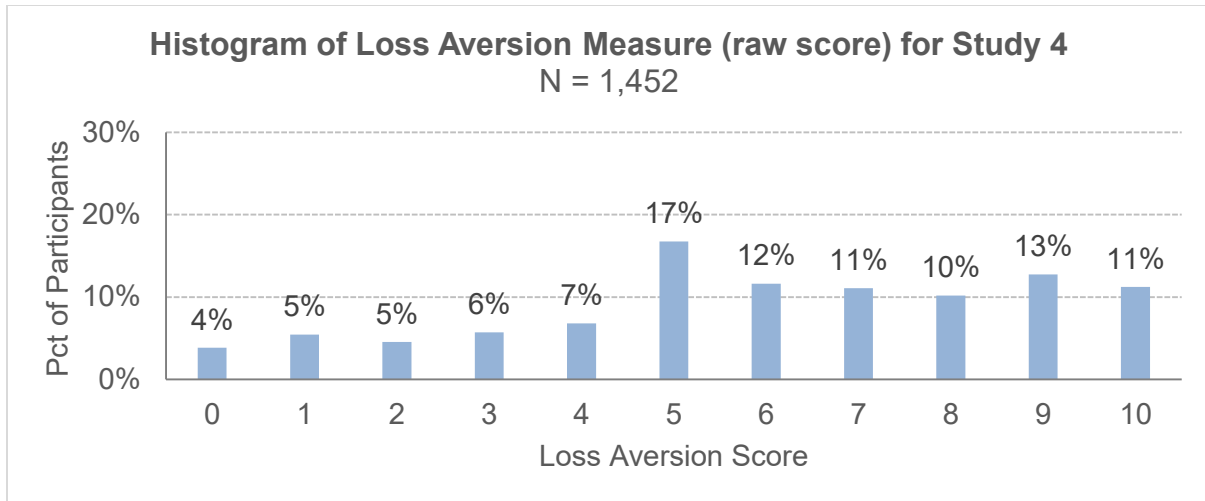
	45%	10%	45%
<b>Gamble 1</b>	\$600	\$0	-\$600
<b>Gamble 2</b>	\$400	\$0	-\$400

	45%	10%	45%
<b>Gamble 1</b>	\$400	\$0	-\$400
<b>Gamble 2</b>	\$700	\$0	-\$600

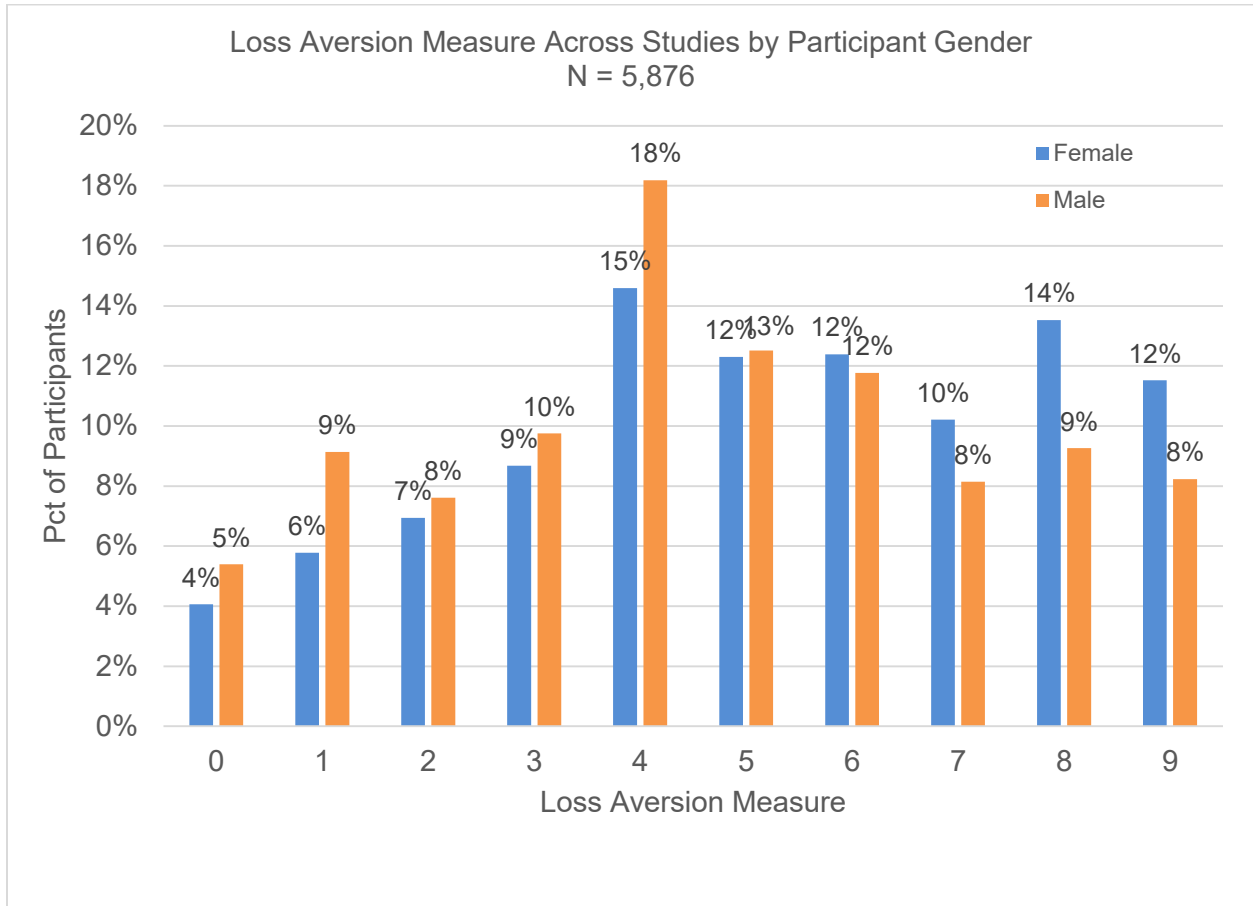
	45%	10%	45%
<b>Gamble 1</b>	-\$400	\$0	\$400
<b>Gamble 2</b>	-\$600	\$0	\$900

**Figure 2: Histograms of loss aversion raw scores, per study, for Studies 1-6**

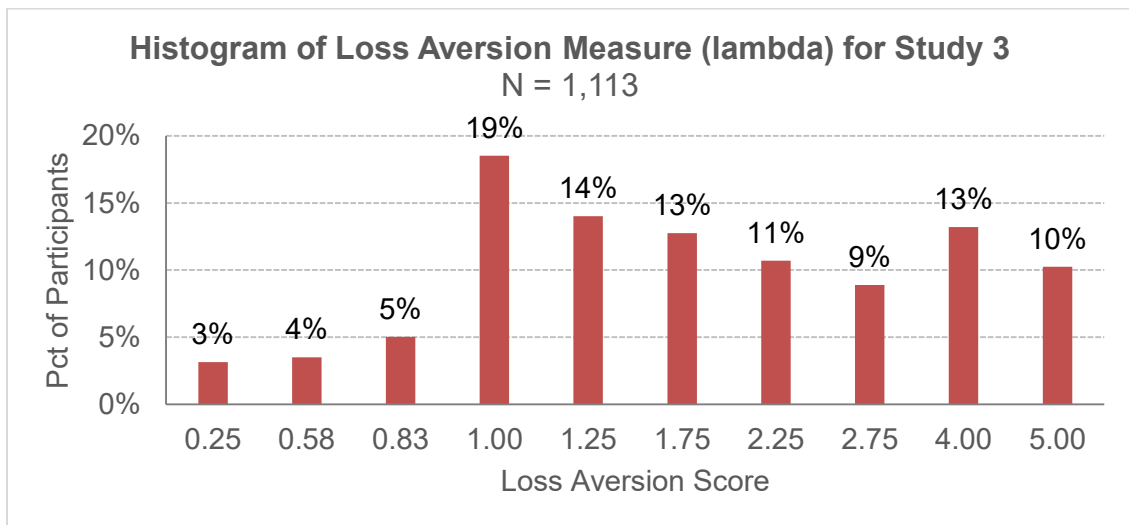
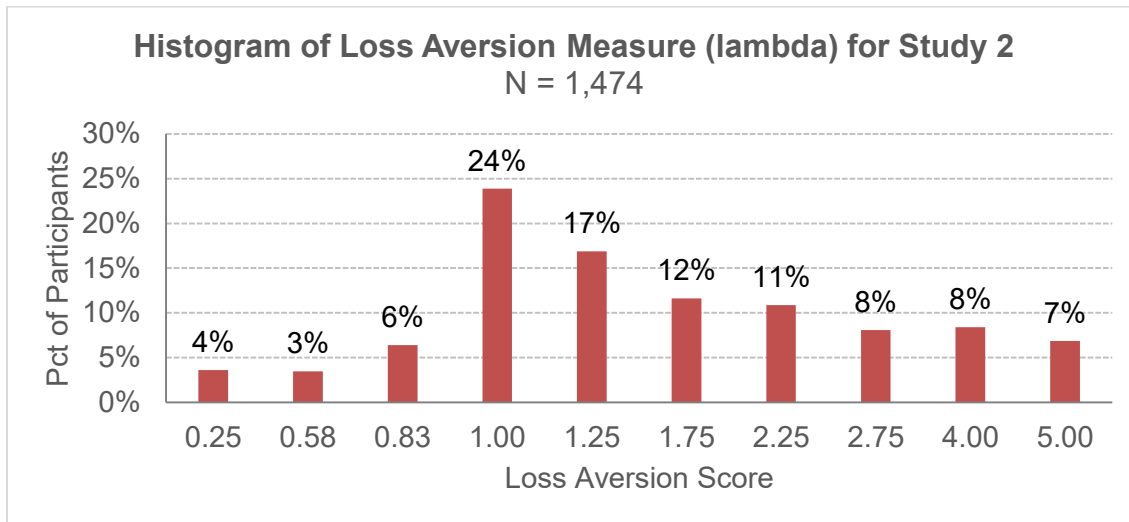
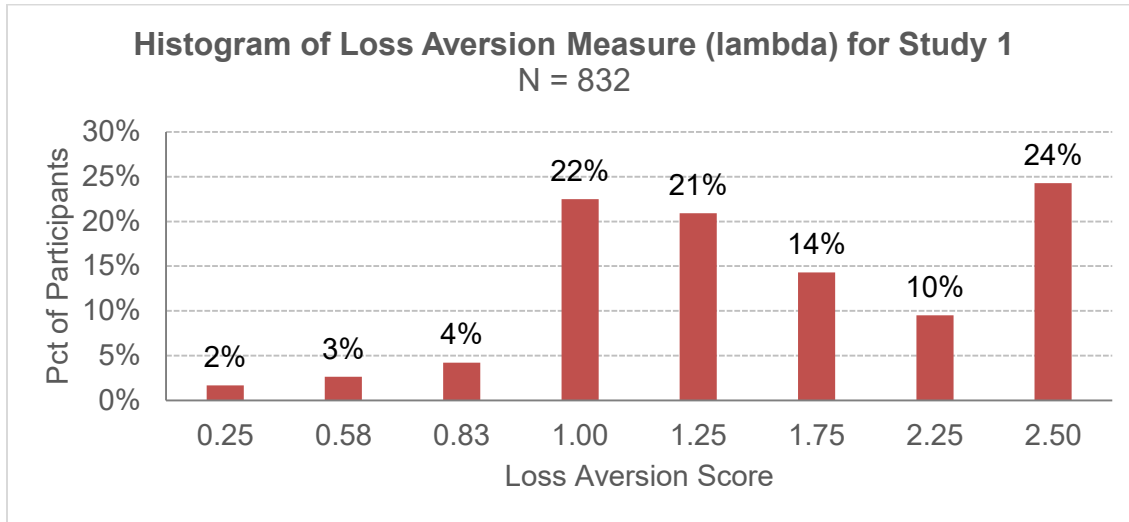


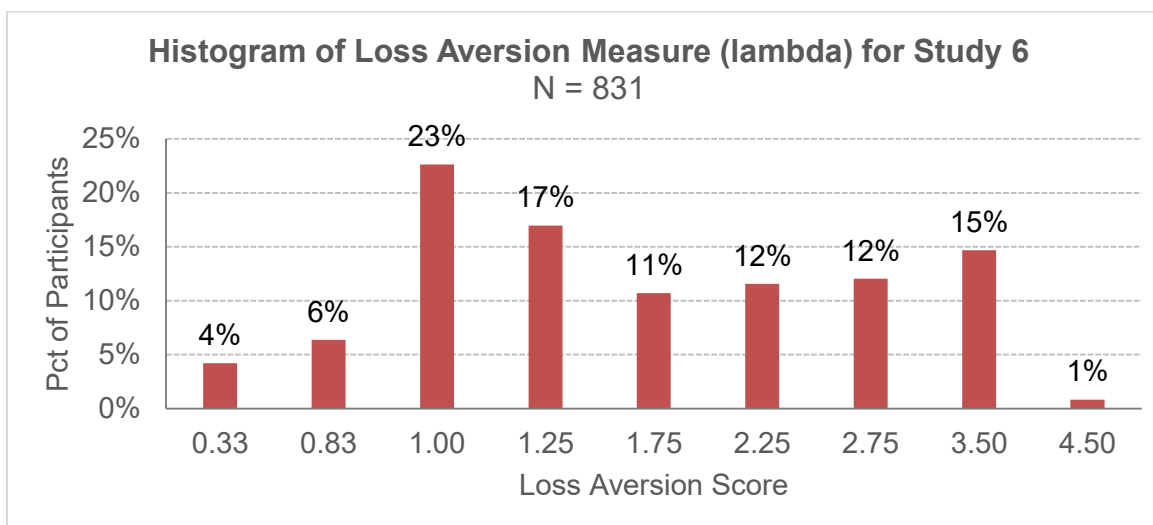
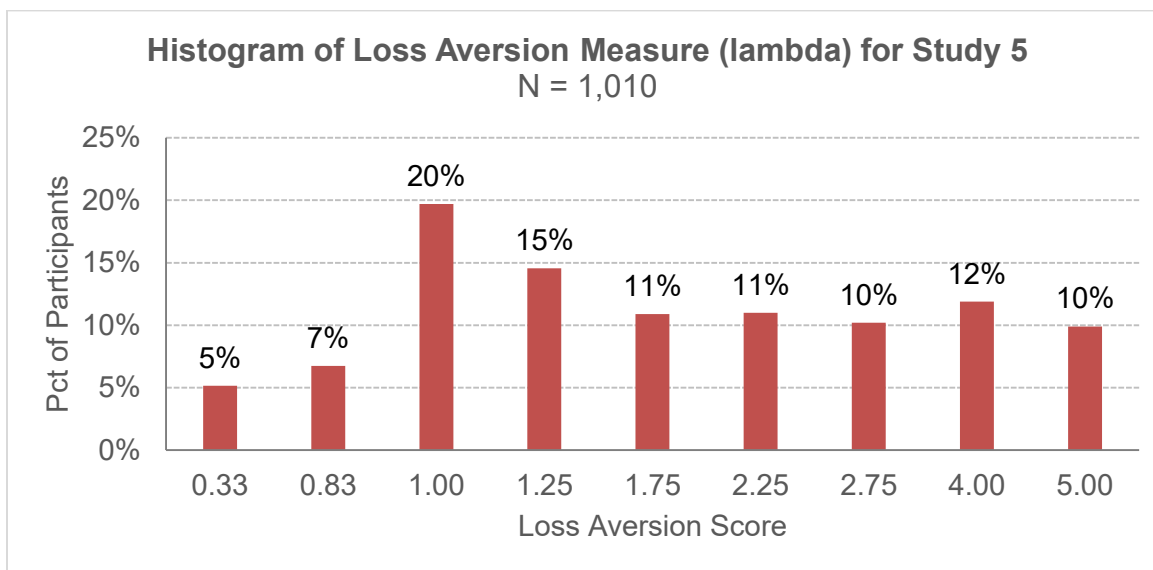
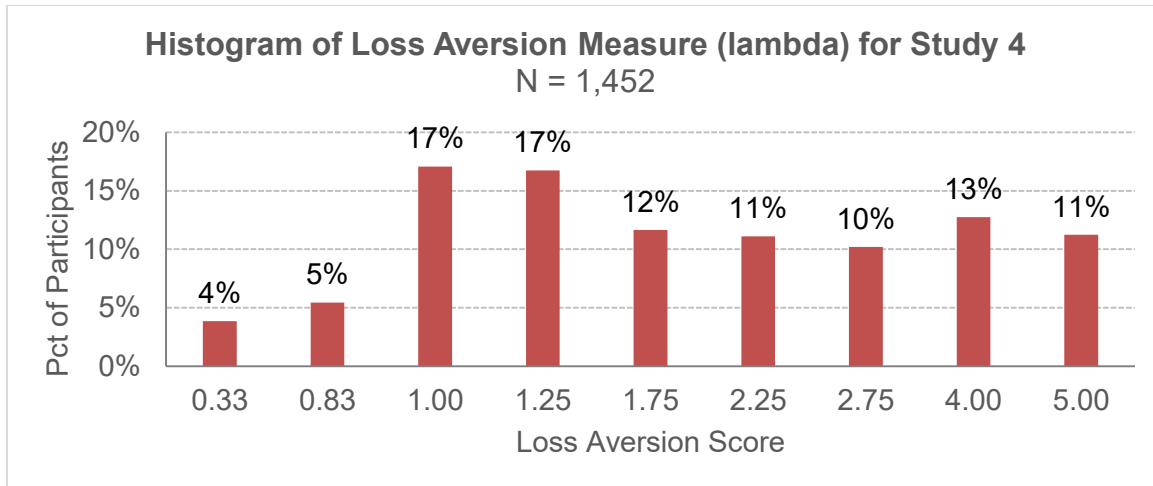


**Figure 3: Histogram of loss aversion raw scores for aggregated results Studies 2-6, by gender**

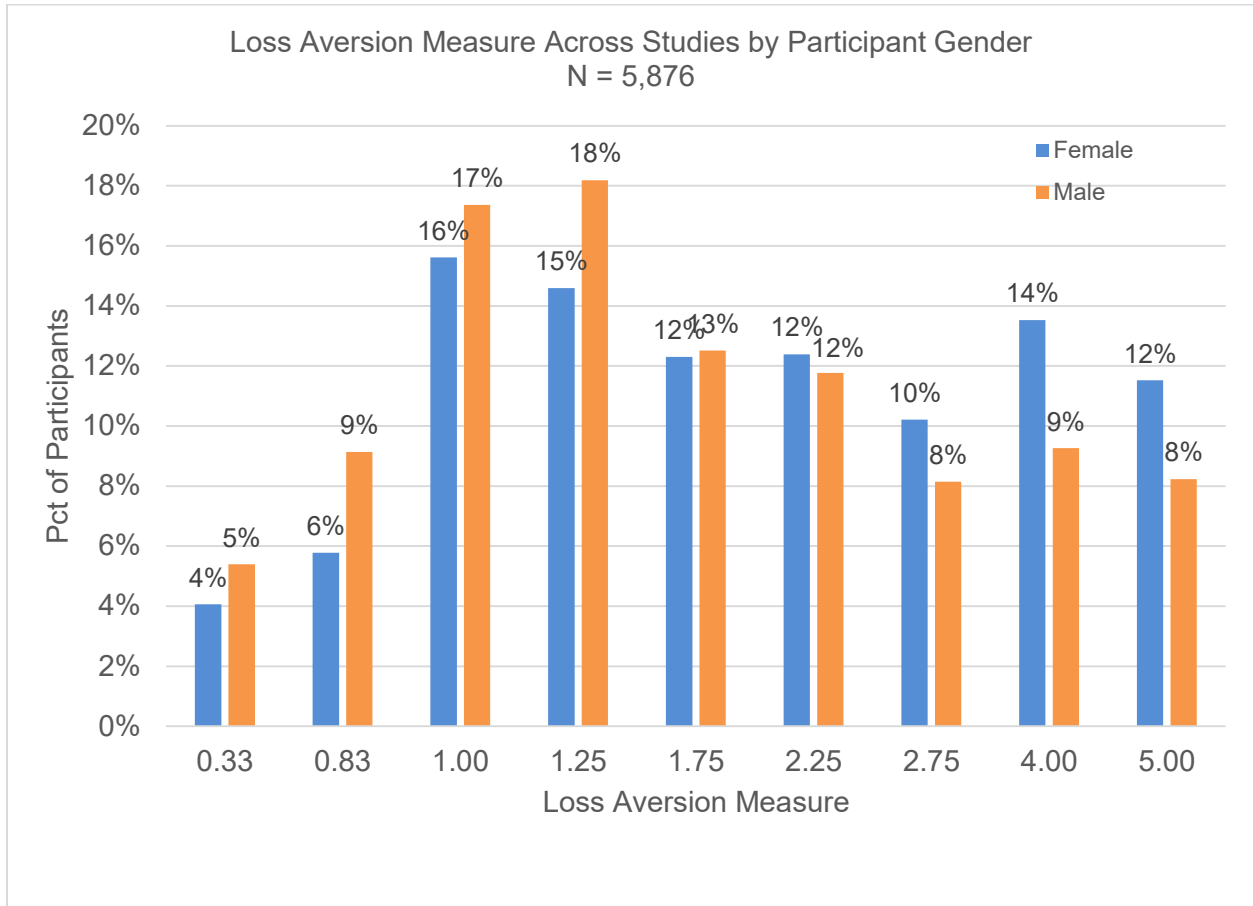


**Figure 4: Histograms of loss aversion lambdas, per study, for Studies 1-6**





**Figure 5: Histogram of loss aversion lambdas for aggregated results Studies 2-6, by gender**



**Figure 6: Comparison of loss aversion raw scores by probability manipulation, Study 4**

