How Malleable are Risk Preferences and Loss Aversion?

Jonathan P. Beauchamp
Harvard University

Daniel J. Benjamin
Cornell University

Christopher F. Chabris
Union College

David I. Laibson*
Harvard University

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Abstract

We estimate risk aversion and loss aversion for 550 experimental participants using the Multiple Price List elicitation method. On each screen of the experiment, participants make seven binary choices between a prospect that is held fixed and a sequence of seven (sure-thing) alternative outcomes. In a between-subject design, the set of alternative outcomes is varied by holding the lowest and highest outcomes fixed and changing the five intermediate outcomes. These manipulations robustly change measured risk preferences. For prospects in the gain domain, as the intermediate alternative outcomes are decreased – holding the endpoints fixed – the participants' choices become significantly more risk averse, both statistically and economically. We find analogous effects for prospects that are in the domain of losses and for prospects that are mixed (with gains and losses). In addition, randomly chosen participants are told the expected value of the prospects. This expected-value information does not affect participants' choices.

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1 Introduction

An influential and large body of research in experimental economics measures risk aversion and loss aversion (e.g., Kahneman and Tversky 1979, Tversky and Kahneman 1992, Barsky et al 1997, Harrison et al 2007, Andersen et al 2008, Bruhin et al 2010). In many experiments in this literature, economists infer preferences from lists of binary lottery choices: i.e., the multiple price list method (e.g., Holt and Laury 2002). These inferences may be affected by framing effects that are implicitly introduced by the experimenter. In this paper, in an experiment with 550 participants, we study the extent to which inferences about risk aversion and loss aversion parameters are affected by two kinds of framing effects.

First, we study whether it matters if experimental participants are told the expected value of the risky prospects. This manipulation is hypothesized to *anchor* the participants on the expected value (e.g., Tversky and Kahneman, 1974) and nudge their preferences toward risk neutrality. Surprisingly to us, however, in no case do we find evidence that this expected-value framing effect is quantitatively important. Providing expected value information does not affect measured risk aversion for prospects in the domain of gains, nor measured risk seeking for prospects in the domain of losses, nor measured loss aversion in the case of mixed (gain/loss) prospects.

Second, we study whether the set of choices in a multiple price list matters for preference elicitation. To understand the potential role of such a framing effect, consider the following example, which is part of the experiment reported in the current paper (and typical of other multiple-price-list risk aversion experiments). As shown on the screenshot below, a participant is asked to make seven binary choices. Each of the seven choices is between a risky prospect – a 10% chance of gaining \$100 and a 90% chance of gaining \$50 – and a changing (sure-thing) alternative. The prospect is held fixed across the seven choices, while the alternative varies from high to low.

A gamble gives you a 10% chance of gaining $100 and a 90% chance of gaining $50 instead.

Would you rather...

(a)	Take the gamble	OR	Gain $57.00
(b)	Take the gamble	OR	Gain $55.60
(c)	Take the gamble	OR	Gain $54.70
(d)	Take the gamble	OR	Gain $54.20
(e)	Take the gamble	OR	Gain $53.90
(f)	Take the gamble	OR	Gain $53.70
(g)	Take the gamble	OR	Gain $53.60

For illustrative purposes, assume that the participant is truly *risk neutral.* Consequently, if she took the time to think carefully about her decision, she would accept the alternatives in rows (a) and (b) and reject the alternatives in rows (c) through (g). However, for a variety of reasons, rational or irrational, the participant might instead be prone to switch closer to the middle option (d). For example, the participant might rationally infer that the experimenter has designed the choices so that the middle options are the best switch points for typical participants (c.f., Kamenica, 2008).[1] Alternatively – and more plausibly, since most participants probably know their own preferences and do not need to infer them – a participant may rely on the time-saving heuristic of choosing one of the middle options. Either way, suppose that the participant accepts the alternative outcome in rows (a), (b), and (c), and accepts the prospect in rows (d) through (g). With the resulting experimental data, an outside observer will conclude that the participant is risk averse, since the participant prefers the sure thing of $54.70 to a risky prospect with an expected value of $55. However, the inference about risk aversion may be misleading. In our example, the apparent risk aversion was induced by the experimental design and not by the participants' deep preferences.

To study effects of this type, we experimentally vary the middle options in a multiple price list using *scale manipulations*, in which we hold the endpoints of the multiple price list fixed and manipulate the locations of the intermediate points within the scale. For example, compare the

[1] Indeed, if the experimenter is trying to measure inter-subject differences and has designed the experiment to maximize power, then the middle options *should* be chosen to equal the experimenter's best guess of the optimal switch points for the typical participant. In this way, the framing effect we study may cause experimenters, by their choice of experimental design, to bias their results in the direction of reinforcing their prior beliefs about the degree of participants' risk aversion.

screenshot above to the screenshot that follows, which has new alternative outcomes in rows (b) through (e), although the end points – rows (a) and (f) – are the same. With respect to this second screenshot, an agent who acts as if the middle option – row (d) – is her indifference point would be judged to be risk seeking.

A gamble gives you a 10% chance of gaining $100 and a 90% chance of gaining $50 instead.

Would you rather...

(a)	Take the gamble	OR	Gain $57.00
(b)	Take the gamble	OR	Gain $56.90
(c)	Take the gamble	OR	Gain $56.70
(d)	Take the gamble	OR	Gain $56.40
(e)	Take the gamble	OR	Gain $55.90
(f)	Take the gamble	OR	Gain $55.00
(g)	Take the gamble	OR	Gain $53.60

Using intermediate-value manipulations with fixed end-points (in a between-subject design), we generate five different scale treatment conditions. We find that these manipulations robustly change measured risk aversion and loss aversion. The effects always go in the direction we hypothesize. For example, for prospects in the gain domain (as in the above example), as the sure-thing options in the middle of the multiple price list decrease, measured preferences become more risk averse. We also document analogous effects for prospects that are exclusively in the domain of losses and for prospects that are mixed (with gains and losses).

In the domain of mixed prospects, when we use the scale manipulation that is hypothesized to produce the most risk tolerance, we almost completely eliminate loss aversion – partly because loss aversion is generally weak in our data, and partly because the scale manipulation is strong. Since risky-choice settings differ from each other in the spacing of the options, our results suggest that researchers should be cautious in assuming that preference parameter values that are estimated in a particular experiment will accurately describe choices in other risky choice settings.

While we are not aware of any existing work on how these framing effects might matter for estimated loss aversion, there is prior work in the context of risk aversion over gains. Like us, Lichtenstein, Slovic, and Zink (1969) and Montgomery and Adelbratt (1982) both conclude that there is no effect of telling participants the expected values of gambles. But in both papers, the data are difficult to interpret because there is a small, statistically insignificant tendency for participants to behave more risk-neutrally when they are told the expected value, and the authors' conclusions are based primarily on the fact that most participants self-report not using the expected value information. Consistent with what we find, Birnbaum (1992) and Stewert, Chater, Stott, and Reimers (2003) conclude that scaling manipulations affect risk aversion. It is difficult to interpret the magnitude of the effect, however, because the choices are hypothetical and because the measures of risk aversion are not easy to translate into preference parameters. There are several experiments conducted with incentives and analyzed in terms of preference parameters, but these do not paint a clear picture: Harrison, Lau, Rutström, and Sullivan (2005) find that risk aversion can be increased or decreased by an appropriate scaling manipulation; Andersen, Harrison, Lau, and Rutström (2006) find that risk aversion can be decreased but not increased; Harrison, Lau, and Rutström (2007) find the opposite; and Harrison, List, and Towe (2007) find that a scaling manipulation intended to increase risk aversion does so, but a scaling manipulation intended to decrease risk aversion actually increases it. Because our sample is much larger than in this existing work, we are able to estimate precise, robust effects. Because we pose gambles involving losses as well as gambles involving gains, we can study the effect of scale manipulations not only on risk aversion over gains, but also on risk aversion over losses and on loss aversion. All of our scale manipulations have the same effect: experimental choices are pulled toward the middle of the multiple price list, accordingly influencing estimates of risk aversion and loss aversion.

We focus this paper on the effect of our framing manipulations, but our preference parameter estimates for Cumulative Prospect Theory (Tversky and Kahneman, 1992) are of independent interest (for reviews, of previous work see Booij, van Praag, and, Kullen 2010 and Abdellaoui, Bleichrodt, and Paraschiv, 2007). In particular, while the widely accepted stylized fact in the theoretical and applied literatures on loss aversion is that the coefficient of loss aversion is $\lambda = 2.25$ (as found by Tversky and Kahneman, 1992), we find a mean loss aversion parameter of 1.25 and a median of only 1.04, which is close to the limiting case of no loss aversion ($\lambda = 1$).[2] While we are intrigued by this finding, we caution that our loss aversion estimates are identified from a relatively small number of gambles that involve both gains and losses.

[2] This finding accords with Wakker's (2010, p.265) conclusion about the experimental evidence on loss aversion: "loss aversion is volatile and depends much on framing, and [the loss aversion parameter] $\lambda = 2.25$ cannot have the status of a universal constant."

The rest of the paper is organized as follows. In Section 2 we discuss our four formal hypotheses and the experimental design that we use to test those hypotheses. In Section 3 we present our estimation strategy. We report our results in Section 4. In Section 5 we conclude with three cautionary implications.

2 Experiment

2.1 Design

Our experiment studies four kinds of binary choices between lotteries. We follow Kahneman and Tversky and refer to our lotteries as prospects. In Part A we study binary choices between a prospect in the gain domain and a sure gain. In Part B, we study binary choices between a prospect in the loss domain and a sure loss. In Part C we study binary choices between a gain/loss prospect and a sure thing of 0. In Part D we study binary choices between two prospects. We provide more detailed descriptions of these lotteries below (and in Appendix I).

Throughout the experiment, we employ the multiple price list elicitation method (similar to Holt and Laury, 2002).[3] At the top of each computer screen, a "fixed" prospect is presented. The "fixed" prospect is usually a non-degenerate lottery; it is "fixed" in the sense that it is an option in *all* of the binary choices on that screen. (The fixed prospect changes *across* screens.) On each screen, seven binary choices are listed below the fixed prospect. Each binary choice is made between the fixed prospect (at the top of the screen) and what we refer to as an *alternative*. The alternatives vary within a screen – one alternative for each of the seven binary choices. Screenshots of the experiment are shown in the Introduction as well as in the Appendix. In most cases, the seven alternatives are sure-things, which we refer to as "alternative outcomes." However, in some cases – explained below – the alternatives are not sure-things.

Our set-up for eliciting risk preferences is standard. Indeed, we designed many details of our experiment – such as giving participants choices between a fixed prospect and seven alternative

[3] While our procedure is a Multiple Price List, it is not the same as Holt and Laury (2002). Holt and Laury offer their participants choices between a fixed gamble and a set of alternative gambles that vary in the probability of the good outcome. In contrast, as discussed below, our procedure closely follows Tversky and Kahneman (1992). Like in Holt and Laury, we sometimes offer a choice between a fixed gamble and a set of alternative gambles, but unlike in Holt and Laury, sometimes the fixed gamble is degenerate (i.e., a sure thing). Moreover, unlike in Holt and Laury, the alternative gambles vary in the payoff amounts rather than in the probabilities.

outcomes – to closely follow Tversky and Kahneman's (1992; henceforth T&K) experiment in their paper on Cumulative Prospect Theory. Moreover, our set of fixed prospects is identical to the set used by T&K. Further mimicking T&K's procedure, our computer program enforces consistency in the participants' choices by requiring participants to respond monotonically to the seven choices on the screen.[4] Our algorithm for generating the seven alternative outcomes is explained in Section 2.2. We list the complete set of fixed prospects and alternatives in Online Appendix I.[5]

Each participant faces a total of 64 screens in the experiment, each of which contains seven choices between a fixed prospect and alternatives. There are four types of screens that differ from each other in the kinds of prospects and alternatives they present. To make it easier for participants to correctly understand the choices we are presenting to them, we divide the experiment into four sequential parts (each with their own instruction screen); each part contains a single type of fixed prospect and a single type of alternative. The order of the screens is randomized within each part; half the participants complete the screens in that order, and the other half complete the screens in the reverse order.

In Part A, the fixed prospects are in the gain domain, and the alternatives are sure gains (as in the example screens in the Introduction). There are 28 fixed prospects that differ both in probabilities and money amounts, which range from \$0 to \$400. The seven alternative outcomes for each fixed prospect range from the certainty equivalent for a CRRA expected-utility-maximizer with CRRA parameter $\gamma = 0.99$ to the fixed prospect's certainty equivalent for $\gamma = -1$ (which is risk seeking).[6] This allows us to cover the relevant range of alternative outcomes for each fixed prospect

[4] More precisely, participants only have to select the circle corresponding to the lowest alternative outcome they prefer to the fixed prospect, as well as the circle corresponding to taking the fixed prospect in the highest row in which they prefer doing so; an auto-fill feature of the computer program fills the other circles.

[5] Our procedure differs from T&K's in three important ways. First, our algorithm for generating the seven alternative outcomes necessarily differs from theirs because theirs is described in too little detail to imitate it (and the actual values are not reported). Second, while their gambles were all hypothetical, our "Part A" gambles (discussed below) were incentivized. Third, for each screen, T&K implement a two-step procedure for identifying risk preferences: after finding the point at which participants switch from preferring the alternative outcomes to preferring the fixed prospect, they have the participant make choices between the fixed prospect and a second set of seven alternative outcomes, linearly spaced between a value 25% higher than the lowest amount accepted in the first set and a value 25% lower than the highest amount rejected. We avoid this two-step procedure (which Harrison, Lau and Rutström, 2007, call an "Iterative Multiple Price List") partly because it takes more experimental time to implement and partly because it is generally not incentive compatible. Specifically, the experimental participant may have an incentive to distort his/her indifference point for the alternative outcome in the first stage toward a higher monetary value in order to have high monetary values for the alternative outcomes in the second stage.

[6] We use $\gamma = 0.99$, rather than $\gamma = 1$, to generate our lowest alternative outcomes because $\gamma = 1$ corresponds to log utility and implies certainty equivalents of \$0 for any prospect with a chance of a \$0 outcome, regardless of how small the probability of that \$0 outcome. $\gamma = 1$ would generate much larger, and less relevant, ranges of alternative outcomes for such prospects.

and thus to obtain precise estimates without using T&K's two-step procedure. Each participant is told that there is a 1/6 chance that one of his or her choices in Part A will be randomly selected and implemented for real stakes at the end of the experiment. The expected payout for a risk neutral participant who rolls a 6 is about \$100. The remaining parts of the experiments involve hypothetical stakes.

In Part B, the fixed prospects now have outcomes in the loss domain, and the alternative outcomes are sure losses. The 28 prospects and alternative outcomes in Part B are identical to those in Part A but with all dollar amounts multiplied by -1.

Parts C and D depart somewhat from the baseline format of our experiment, in that the alternatives are now risky prospects rather than sure things. Moreover, in Part C, the fixed prospect is the degenerate prospect of a sure thing of \$0 and is not listed at the top of each screen. The seven alternatives on each of the four screens in Part C are mixed prospects that have a 50% chance of a loss and 50% chance of a gain. For example, one of the screens in Part C is:

A gamble gives you a 50% chance of losing \$150 and ...

(a)	... a 50% chance of gaining \$0.00 instead.	Take the gamble	OR	Don't take the gamble
(b)	... a 50% chance of gaining \$14.90 instead.	Take the gamble	OR	Don't take the gamble
(c)	... a 50% chance of gaining \$39.60 instead.	Take the gamble	OR	Don't take the gamble
(d)	... a 50% chance of gaining \$80.60 instead.	Take the gamble	OR	Don't take the gamble
(e)	... a 50% chance of gaining \$148.80 instead.	Take the gamble	OR	Don't take the gamble
(f)	... a 50% chance of gaining \$262.00 instead.	Take the gamble	OR	Don't take the gamble
(g)	... a 50% chance of gaining \$450.00 instead.	Take the gamble	OR	Don't take the gamble

On any given screen, the amount of the possible loss is fixed and the seven mixed prospects involve different amounts of the possible gain. Part C has four screens, each with a different loss amount: \$25, \$50, \$100, and \$150.

Part D also comprises four screens, each containing choices between a fixed 50%-50% risky prospect and seven alternative 50%-50% risky prospects. On two of the four screens, both the fixed and the alternative prospects are mixed – i.e., one possible outcome is a gain and the other is a loss – as in the following:

Gamble 1 gives you a 50% chance of gaining $100 and a 50% chance of gaining $300.

Gamble 2 gives you a 50% chance of gaining $25 and ...

(a)	... a 50% chance of gaining $525.00 instead.	Take gamble 1	OR	Take gamble 2
(b)	... a 50% chance of gaining $431.00 instead.	Take gamble 1	OR	Take gamble 2
(c)	... a 50% chance of gaining $374.40 instead.	Take gamble 1	OR	Take gamble 2
(d)	... a 50% chance of gaining $340.30 instead.	Take gamble 1	OR	Take gamble 2
(e)	... a 50% chance of gaining $319.80 instead.	Take gamble 1	OR	Take gamble 2
(f)	... a 50% chance of gaining $307.40 instead.	Take gamble 1	OR	Take gamble 2
(g)	... a 50% chance of gaining $300.00 instead.	Take gamble 1	OR	Take gamble 2

On the other two screens, the fixed and the alternative prospects involve only gains. On any given screen, one of the two possible realizations of the alternative prospects is fixed, and the seven choices on the screen involve different amounts of the other possible realization of that prospect. For each screen in Parts C and D, the varying amounts of the alternative prospects range from the amount that would make an individual with linear utility, no probability distortion, and loss insensitivity ($\lambda = 0$) indifferent to the fixed prospect to the amount that would make an individual with loss aversion $\lambda = 3$ indifferent.

After Parts A-D, participants complete a brief questionnaire that asks age, race, educational background, standardized test scores, ZIP code of permanent residence, and parents' income (if the participant is a student) or own income (if not a student). It also asks a few self-reported behavioral questions, including general willingness to take risks and frequency of gambling.

2.2 Treatments

Our experiment is motivated by two questions: How does the set of alternatives offered to participants affect their risk-taking behavior? And how does reporting the expected value of the prospects affect behavior?

To address the first question, we randomly assign each participant to one of five treatment conditions, labelled Pull -2, Pull -1, Pull 0, Pull 1, and Pull 2. The five treatments are identical in the set of fixed prospects and in the *first* and *seventh* alternative on each screen, but differ from each other in the second through sixth alternatives, which we call the 'intermediate' alternatives.

Specifically, they differ only in the selection of the *second* through *sixth* alternative outcomes. For instance, in Part A for the illustrative fixed prospect above – a 10% chance of gaining \$100 and a 90% chance of gaining \$50 – the alternative outcomes (a) through (g) are given in the positive half of Figure 1, by treatment condition.

In the Pull 0 treatment, the alternative outcomes are evenly spaced, aside from rounding to the nearest \$0.10, from the low amount of \$53.60 to the high amount of \$57.00. In the Pull 1 and the Pull 2 treatments, the alternative outcomes are more densely concentrated at monetary amounts close to zero. These treatments are designed to resemble T&K's experiment, in which the second through sixth alternative outcomes are "logarithmically spaced between the extreme outcomes of the prospect" (T&K, p. 305).[7] Conversely, in the Pull -1 and Pull -2 treatments, the alternative outcomes are more densely concentrated at money amounts *away* from zero. Pull 2 and Pull -2 are more skewed than Pull 1 and Pull -1. We refer to the different treatments as "Pulls" to convey the intuition that they pull the distributions of the alternative outcomes toward zero (for the positive Pulls) or away from zero (for the negative Pulls).

As mentioned above, Part B mirrors Part A but with all amounts multiplied by -1 (see the negative half of Figure 1). Again, Pull 1 and Pull 2 pull the distribution of alternative outcomes toward zero, and Pull -1 and Pull -2 push the distribution of outcomes away from zero. Again, Pull 2 and Pull -2 correspond to the most asymmetric distortions (relative to the evenly spaced case). In Parts C and D, Pull 1 and Pull 2 pull the distribution of the varying amounts of the alternative prospect on each screen toward zero, and Pull -1 and Pull -2 do the opposite. Online Appendix I shows the complete set of fixed prospects and alternatives for each Pull treatment.[8] Each participant is assigned to the same pull treatment for all screens and all parts (A-D) of the experiments.

Our pull treatment is designed to investigate context effects on measured risk preferences. Con-

[7] T&K do not provide further details on the alternative outcomes, so we cannot exactly mimic their procedure.

[8] We use the following algorithm to determine the second through sixth alternative outcomes in Pull 1 and Pull 2 for Part A. Label the alternative outcomes for screen q, in decreasing monetary amounts, x_{q1}, x_{q2},...,x_{q7}. First, x_{q1} and x_{q7} are obtained as described in the previous subsection. Define $\Delta_q \equiv x_{q1} - x_{q7}$. Second, for $k = 0.3$ (for Pull 1) and $k = 0.05$ (for Pull 2), solve $(1+a)^6 k\Delta_q = (1+k)\Delta_q$ for a to find the five points that yield a log scale from $k\Delta_q$ to $(1+k)\Delta_q$: $z_i = (1+a)^{(i-1)} k\Delta_q$, $i = 2, ..., 6$. Third, obtain the second through sixth alternative outcomes for screen q by "shifting" the log scale so that it starts at x_{q1} instead of $k\Delta_q$: $x_{qi} = z_i + (x_{q1} - k\Delta_q)$, $i = 2, ..., 6$, and round to the nearest dime. In Pull -1 and Pull -2, the spacing between x_{qi} and $x_{q(i+1)}$ is equal to the spacing between $x_{q(7-i)}$ and $x_{q(7-i+1)}$ $(i = 1, ..., 6)$ in Pull 1 and Pull 2, respectively. For Parts C and D, we use the same algorithm to determine the unfixed parts of the second through sixth alternative prospects. The amounts for Part B are identical to the amounts for Part A, multiplied by -1.

text effects refer to the influence of the context in which a stimulus appears on the perception of the stimulus (Pomerantz, 2006). Classic examples in psychology include loudness scales (Garner, 1954) and the brightness contrast, whereby the brightness of a stimulus depends both on its own luminance and on that of the surrounding stimuli. In economics, Kamenica (2008) shows that context can convey valuable information to consumers in a market equilibrium. Tversky and Simonson (1993) review experimental evidence for the influence of context on choice. We hypothesize that the varying distributions of alternatives across treatment – and the associated varying values of the middle alternatives – generate context effects on participants' choices.

For instance, consider the example in the introduction, which features a fixed prospect with outcomes in the gain domain and sure-thing alternatives that are also in the gain domain. Moving across the range of treatments from Pull -2 to Pull 2 is hypothesized to raise estimated risk aversion. For example, in the Pull 2 treatment (first screen shot) the intermediate alternatives are shifted closer to zero, coaxing subjects to choose an indifference point that is closer to zero, thereby implying a relatively high level of risk aversion. By contrast, in the Pull -2 treatment (the second screen shot), the intermediate alternatives are shifted away from zero, coaxing subjects to choose an indifference point that is farther from zero, thereby implying a relatively low level of risk aversion.

The hypothesized effect of the pull treatments on estimated relative risk *seeking* in the loss domain is analogous. To build intuition, consider a fixed prospect that has outcomes in the loss domain (cf. Part B of the experiment). Moving across the range of treatments from Pull -2 to Pull 2 is now hypothesized to raise estimated risk *seeking*. For example, in the Pull 2 treatment the intermediate alternatives are all negative and shifted relatively close to zero, coaxing subjects to choose an indifference point that is closer to zero, thereby implying a relatively high level of risk seeking. By contrast, in the Pull -2 treatment, the intermediate alternatives are all negative and shifted away from zero, coaxing subjects to choose an indifference point that is farther from zero, thereby implying a relatively low level of risk seeking.

Similar considerations imply that moving across the range of treatments from Pull -2 to Pull 2 is predicted to lower the level of estimated loss aversion ($\hat{\lambda}$). As the pull variable rises, the intermediate alternatives shift toward the case of risk neutrality.

In sum, we make the following hypotheses:

Hypothesis 1: Relative risk aversion in the gain domain ($\hat{\gamma}^+$) and relative risk seeking in the loss domain ($\hat{\gamma}^-$) will both be increasing in Pull.

Hypothesis 2: Loss aversion ($\hat{\lambda}$) will be decreasing in Pull.

To study the effect of informing participants about expected values, we independently manipulate the presence (or absence) of expected value information. Because we anticipated that many participants would be unfamiliar with the concept of expected value, simple language is used in the "EV treatment" to describe the expected value of a prospect. For instance, in Part A, the following appears below the fixed prospect at the top of the screen: "On average, you would gain $55 from taking this gamble." Loss aversion and considerable risk aversion over small-stakes prospects are hard to reconcile with expected utility theory (Rabin, 2000). To the extent that such behavior is the consequence of cognitive errors in comprehending a prospect, displaying useful information to characterize a prospect – such as its expected value – may decrease loss aversion and small-stake risk aversion (see Benjamin, Brown, and Shapiro, 2006, for a similar treatment). In addition, displaying the expected value may anchor the participants on the expected value (Tversky and Kahneman, 1974) and make their preferences more risk neutral. We therefore hypothesize:

Hypothesis 3: $\hat{\gamma}^+$ and $\hat{\gamma}^-$ will shift toward zero in the EV treatment.

Hypothesis 4: $\hat{\lambda}$ will shift toward one in the EV treatment.

2.3 Procedures and Sample

The experiment was run online from March 11 to March 20, 2010. Our sample was drawn from the Harvard Business School Computer Lab for Experimental Research's (CLER) online subject pool database. This database contains several thousand participants nationwide who are available to participate in online studies. Participants must be at least 18 years old, must be eligible to receive payment in the US, and must not be on Harvard University's regular payroll; they are mainly recruited through flyer postings around neighboring campuses.

At the launch of the experiment, the CLER lab posted a description to advertise the experiment to the members of the online subject pool database; any member of the pool could then participate until a sample size of 550 was reached. Each participant was pseudo-randomly assigned to one

Pull and to one EV treatment to ensure that our treatments were well-balanced. A total of 521 participants completed all four parts of the experiment. The mean response time for the participants who completed the experiment in less than one hour was 32 minutes.[9]

In addition to the above-described incentive payment for Part A, participants were paid a total of \$5 if they began the experiment; \$7 if they completed Part A; \$9 if they completed Parts A and B; \$11 if they completed Parts A, B, and C; and \$15 if they completed all four parts of the experiment.

3 Estimation

A natural first analysis of our data would be to examine the effects of our manipulations on the average number of risk averse responses. Unfortunately, that empirical strategy would not work for studying the effect of the Pull treatments. Suppose we find that participants make a greater number of risk averse choices when the alternative outcomes are more densely concentrated at lower money amounts. Such a finding would be consistent with Hypotheses 1 and 2 but could also be due to a mechanical effect: an individual with any fixed level of risk aversion (unaffected by treatment condition) would make a greater number of risk averse choices when more of the gambles have alternative outcomes with low money amounts.

Instead, we estimate the parameters of Cumulative Prospect Theory (CPT) preferences via Maximum Likelihood Estimation at the individual level (which we can do because each participant makes many choices). Our empirical strategy is to test whether these estimated parameters differ systematically across treatment conditions.[10]

For prospect $P = (x_H, p_H; x_L, p_L)$ with probability p_H of monetary outcome x_H and probability

[9] Participants were allowed to complete the experiment in more than one session, so response times were larger than 24 hours for some. Of the 497 participants for whom we analyzed response time data, 405 took less than one hour.

[10] A simpler, commonly-used alternative to Maximum Likelihood Estimation is to calculate for each screen of risky choices the range of coefficients of risk aversion that could rationalize the participant's switchpoint from the fixed prospect to the alternative outcome, and then attribute to the participant the midpoint of the interval. In our context this procedure is problematic for two reasons. First, it does not allow us to account simultaneously for concavity/convexity of the utility function, probability weighting, and loss aversion. Second, even if we focus only on gambles over gains and assume that risk aversion is due solely to concavity of the utility function, there is a similar problem to comparing the number of risk averse choices across treatments:our experimental manipulation of the gap between alternative outcomes would mechanically generate an illusory "treatment effect" on risk aversion, even for a participant whose underlying coefficient of risk aversion were unaffected by the experimental manipulation.

$p_L = 1 - p_H$ of monetary outcome x_L, we assume that utility has the CPT form:

$$(1) \qquad u(P) = \left\{ \begin{array}{ll} \omega^+(p_H) \cdot u^+(x_H) + (1 - \omega^+(p_H)) \cdot u^+(x_L) & \text{if } 0 < x_L < x_H \\ -\omega^-(p_L) \cdot \lambda \cdot u^-(-x_L) - (1 - \omega^-(p_L)) \cdot \lambda \cdot u^-(-x_H) & \text{if } x_L < x_H < 0 \\ \omega^+(p_H) \cdot u^+(x_H) - \omega^-(p_L) \cdot \lambda \cdot u^-(-x_L) & \text{if } x_L < 0 < x_H \end{array} \right\},$$

where $\omega^+(\cdot)$ and $\omega^-(\cdot)$ are the cumulative probability weighting functions for gains and losses, $u^+(\cdot)$ and $u^-(\cdot)$ are the Bernoulli utility functions for gains and losses, and λ is the coefficient of loss aversion.

We assume that $u^+(\cdot)$ and $u^-(\cdot)$ take the CRRA (a.k.a. "power utility") form, $u^+(x) = \frac{x^{1-\gamma^+}}{1-\gamma^+}$ and $u^-(x) = \frac{x^{1-\gamma^-}}{1-\gamma^-}$, as is standard in the literature on CPT (e.g., Trepel, Fox, and Poldrack, 2005; T&K).[11] To estimate the model, we impose the parameter restrictions $\gamma^+, \gamma^- < 1$.[12] Note that γ^+ is the coefficient of relative risk aversion (in the gain domain) and γ^- is the coefficient of relative risk *seeking* (in the loss domain). For our baseline model, we use the Prelec (1998) probability weighting function:

$$\begin{aligned} \omega^+(p) &= \exp(-\beta^+(-\log(p))^{\alpha^+}), \\ \omega^-(p) &= \exp(-\beta^-(-\log(p))^{\alpha^-}), \end{aligned}$$

where $\alpha^+, \beta^+, \alpha^-, \beta^- > 0$. The α and β parameters regulate the curvature and the elevation of $\omega(p)$, respectively. Below, we discuss the robustness of our results to other popular probability weighting functions.

On each screen q of the experiment, a participant makes choices between a fixed prospect,

[11] As Wakker (2010, section 9.6) points out, there are two serious concerns with assuming that $u^+(x) = \frac{x^{1-\gamma^+}}{1-\gamma^+}$ and $u^-(x) = \frac{x^{1-\gamma^-}}{1-\gamma^-}$ when $\gamma^+ \neq \gamma^-$. First, the ratio of disutility from a sure loss of x to utility from a sure gain of x, $\frac{-\lambda u^-(-x)}{u^+(x)}$, is *not* uniformly equal to λ but instead depends on the value of x. Second, for any λ, there exists a range of x values for which this ratio is actually *smaller* than 1, which is the opposite of loss aversion. These problems can make estimates of λ especially sensitive to exactly which prospects are used in the experiment. Because our maximum likelihood procedure generates mean estimates, $\hat{\gamma}^+ = 0.33$ and $\hat{\gamma}^- = 0.31$, that are essentially equal, we believe that these concerns are unlikely to pose a problem for our estimation of λ. To confirm this, we re-estimated all of our main analyses imposing the constraint that $\hat{\gamma}^+ = \hat{\gamma}^-$. The results are virtually identical to those we report.

[12] 15 of the 28 fixed prospects in Part A have a chance of yielding \$0. $\gamma^+ \geq 1$ would imply extremely risk-averse behavior with these 15 prospects, such that any positive alternative sure outcome would always be preferred with probability 1. Every participant in the experiment made choices ruling out such extreme risk aversion (except for a few who picked the alternative sure outcome in every single choice and for whom our ML specification is not identified; those participants are unlikely to have responded seriously to the questions). Analogously for γ^- and behavior in Part B.

denoted P_{qF}, and seven alternative prospects presented in decreasing order of monetary payoff, denoted P_{q1}, P_{q2}, ..., P_{q7}.[13] Recall that the experimental procedure constrained participants to behave consistently: if an individual chooses P_{qi} over P_{qF} for some $i > 1$, then the individual chooses P_{qj} over P_{qF} for all $j < i$. We assume that on any screen q, a participant's choices reflect the participant's preferences plus noise: for all q and i, the participant chooses P_{qi} over P_{qF} if and only if

$$u(P_{qi}) + \varepsilon_{qA} > u\left(P_{qF}\right) + \varepsilon_{qF},$$

where ε_{qF} and ε_{qA} are preference shocks to the fixed prospect and the alternative outcome, respectively.

To derive a likelihood function, we assume $\varepsilon_{qF} - \varepsilon_{qA} \equiv \varepsilon_q \sim N(0, \sigma^2)$. Hence the probability that the participant switches from choosing the alternative prospect when the alternative is P_{qi} to choosing the fixed prospect when the alternative is $P_{q(i+1)}$ is

$$\begin{aligned}
\Pr{}_{q,i,i+1} &\equiv \Pr\left(\text{participant switches between } P_{qi} \text{ and } P_{q(i+1)}\right) \\
&= \Pr(u(P_{q(i+1)}) - u(P_{qF}) < \varepsilon_q < u(P_{qi}) - u(P_{qF})) \\
&= \Phi((u(P_{qi}) - u(P_{qF}))/\sigma) - \Phi((u(P_{q(i+1)}) - u(P_{qF}))/\sigma),
\end{aligned}$$

where $\Phi\left(\cdot\right)$ is the CDF of a standard normal random variable; the probability that the participant always chooses the fixed prospect is $\Pr{}_{q,7,8} \equiv 1 - \Phi((u(P_{q7}) - u(P_{qF}))/\sigma)$; and the probability that the participant always chooses the alternative over the fixed prospect is $\Pr{}_{q,1,2} \equiv \Phi((u(P_{q1}) - u(P_{qF}))/\sigma)$. We assume that σ^2 is a participant-specific parameter, and ε_q is drawn *i.i.d.* for each screen q in the set of Q screens faced by a participant. Thus, the likelihood function for any given participant is:

$$L = \prod_{q \in Q} \prod_{i=0,1,\ldots,7} \left(\Pr{}_{q,i(i+1)}\right)^{1\{\text{switch between } P_{qi} \text{ and } P_{q(i+1)}\}}$$

Our analysis of the data proceeds in two steps. In the first step, we estimate the parameters γ^+, γ^-, α^+, α^-, β^+, β^-, λ, and σ separately for each participant using MLE.[14] For our baseline specification, we use all screens from Parts A-D, with the exception of the two screens of Part D

[13] In Part C, the alternative prospects are presented in increasing order of monetary payoff; we ignore this subtlety here for expositional purposes, but our actual estimation accounted for it.

[14] All empirical analysis was performed using Stata 11.1.

which involve only positive outcomes and which were designed by T&K as placebo tests for loss aversion. Our MLE algorithm converges for 463 of the 521 participants (89%) who completed all parts of the experiment (many of the participants for whom the algorithm does not converge have haphazard response patterns).

In the second step of our analysis, we use OLS to estimate the effects of the treatments on the ML estimates for the participants for whom the algorithm converges.[15] For each parameter separately, we drop the outliers in the distribution of the parameter estimates prior to regressing the parameter estimates on treatment variables. We define the outliers for a given parameter as the estimates lying further away than a cutoff of four standard deviations from the mean in any of six trimming iterations. The distribution of each parameter has a few extreme outliers, and only one or two rounds suffice to cut these outliers for most parameters. For $\hat{\alpha}^+$, $\hat{\alpha}^-$, $\hat{\beta}^+$, $\hat{\beta}^-$, $\hat{\sigma}$, and $\hat{\lambda}$, we also drop negative estimates. For $\hat{\gamma}^+$, $\hat{\gamma}^-$, and $\hat{\lambda}$ – the three parameters on which we focus attention below – we drop a total of 3, 1, and 23 participants, respectively.[16]

Note that because the experiment has a between-subjects design (so that each participant is in exactly one treatment group) and we estimate σ^2 as a participant-specific parameter, our analysis does not impose the restriction that the amount of noise in participants' choices is the same across treatments.[17]

4 Results

We focus our attention on the risk aversion parameters $\hat{\gamma}^+$ and $\hat{\gamma}^-$ and the loss aversion parameter $\hat{\lambda}$ because our *ex ante* hypotheses are about these parameters. At the end of this section, we summarize our findings about the probability weighting function parameters, $\hat{\alpha}^+$, $\hat{\alpha}^-$, $\hat{\beta}^+$, and $\hat{\beta}^-$, and the choice noise parameter, $\hat{\sigma}$.

[15] Logarithms (rather than untransformed levels) of $\hat{\alpha}^+$, $\hat{\alpha}^-$, $\hat{\beta}^+$, $\hat{\beta}^-$, and $\hat{\sigma}$ are taken for this second step, because the empirical distributions of these parameters are lognormal.

[16] For each of these three main parameters of interest, we looked at the effects of changing our cutoff for dropping outliers from four standard deviations from the mean to three, five, and six standard deviations from the mean. In all cases and for all three parameters, the results summarized in Tables 1 and 2 below continue to hold. Details are in Online Appendix III.

[17] Indeed, while in the main text we focus on estimating the effect of treatment condition on $\hat{\gamma}^+$, $\hat{\gamma}^-$, and $\hat{\lambda}$, we report the effect of treatment condition on $\widehat{\sigma}$ in section 4.3 and Online Appendix II. In principle, we could estimate an even more flexible model where the amount of noise for a participant j on screen q, σ^2_{jq}, is the sum of a participant-specific parameter σ^2_j and a screen-specific parameter σ^2_q. We do not pursue this more general approach because, while identified in principle, in practice it would reduce the number of participants for whom the MLE algorithm converges.

4.1 Framing and Risk Aversion

Figure 2 shows histograms of the estimated parameters $\hat{\gamma}^+$ and $\hat{\gamma}^-$ (without the outliers), along with kernel density estimates and normal density functions fitted to the means and variances of the distributions. The vast majority of participants have concave utility in the gain domain ($\hat{\gamma}^+ > 0$) and convex utility in the loss domain ($\hat{\gamma}^- > 0$), in accordance with Cumulative Prospect Theory. The means of $\hat{\gamma}^+$ and $\hat{\gamma}^-$ are 0.33 and 0.31, and the standard deviations are 0.18 and 0.20, respectively. The mean value for $\hat{\gamma}^+$ is near the middle of the range of existing estimates, but the mean value for $\hat{\gamma}^-$ indicates more risk-seeking in losses than is typically found.[18]

As predicted by Hypothesis 1, $\hat{\gamma}^+$ and $\hat{\gamma}^-$ are both increasing with Pull. Figure 3 displays means and 95% confidence intervals for $\hat{\gamma}^+$ and $\hat{\gamma}^-$ by pull treatment. Table 1 shows the results of regressions of $\hat{\gamma}^+$ and $\hat{\gamma}^-$ on treatment variables. In the first and fourth columns, the regressors are a dummy for the expected value treatment and dummies for each of the pull treatments, where the omitted category is Pull 0. Most of the Pull dummies are statistically significant, and an F-test for their joint significance is highly significant for both $\hat{\gamma}^+$ ($p < 0.0001$) and for $\hat{\gamma}^-$ ($p < 0.0001$). In the second and fifth columns, the regressors are a dummy for the expected value treatment and a linear variable equal to Pull. The coefficient on Pull is 0.038 for $\hat{\gamma}^+$ and 0.041 for $\hat{\gamma}^-$, with a standard error of 0.006 in both cases, implying increases of about 0.15 (more than three-quarters of a standard deviation) in $\hat{\gamma}^+$ and $\hat{\gamma}^-$ as we move from Pull -2 to Pull 2. We also note that the R^2 for the four regressions with covariates for the pull treatments in Table 1 are all approximately 10%, which indicates that our treatments explain a considerable part of the variation in estimated risk preferences in our experiment.

While the framing of the choice alternatives has a large effect on risk-taking behavior, it is clear from Figure 3 that participants continue to have concave utility in the gain domain and convex utility in the loss domain even in the most extreme pull treatment (Pull = -2).

Hypothesis 3 predicts that displaying the expected value of the prospects will make participants more risk-neutral, causing γ^+ and γ^- to each move towards 0. Figure 4 shows bar graphs of mean $\hat{\gamma}^+$ and $\hat{\gamma}^-$ by expected value treatment. The third and sixth columns of Table 1 show OLS regressions of $\hat{\gamma}^+$ and $\hat{\gamma}^-$, respectively, on a dummy for the expected value treatment. The effects

[18] Booij, van Praag, and Kullen's (2010) Table 1 reviews existing experimental estimates. Translated into the CRRA functional form we estimate, the range of existing parameter estimates is $\hat{\gamma}^+ \in [0.22, 1)$ and $\hat{\gamma}^- \in [0.72, 1)$..

are not significant and go in opposite directions in the gain and loss domain. The effect of the expected value dummy on $\hat{\gamma}^-$ becomes statistically significant when we additionally control for Pull (the fourth and fifth columns of Table 1), but the effect on $\hat{\gamma}^+$ remains insignificant (the first and second columns of Table 1). Overall then, our data does not support Hypothesis 3.

4.2 Framing and Loss Aversion

Figure 5 shows a histogram of the estimated coefficient of loss aversion $\hat{\lambda}$ (without the outliers) with a kernel density estimate of the distribution. The mean $\hat{\lambda}$ is 1.25, the standard deviation is 0.90, and the median is 1.04. These results match the lower range of loss aversion estimates in the literature.[19] One possible reason for this is that, as described above, the varying parts of the alternative prospects on each screen in Parts C and D range from the amount implied by a loss aversion of zero ($\lambda = 0$) to the amount implied by a loss aversion of three. T&K do not provide the analogous details of their procedure, but it is conceivable that they use a higher range; context effects of a kind similar to those we explore with our pull treatment could be at play here also.

We turn next to testing Hypothesis 2, which predicts that estimated loss aversion will be negatively related to Pull. Figure 6 shows bar graphs of mean $\hat{\lambda}$ by pull treatment, and Table 2 reports the results of regressions of $\hat{\lambda}$ on variables summarizing the different treatments. The F-test for the joint significance of the four Pull dummies in the first column of Table 2 fails to reach significance. The F-test, however, does not take exploit the monotonic effect of Pull on $\hat{\lambda}$. The second column of Table 2 replaces the Pull dummies with a linear Pull regressor. The coefficient of -0.074 on Pull is statistically significant, confirming the relationship that is apparent in Figure 6. These results support Hypothesis 2. The R^2's of the regressions in Table 2 are much lower than those in Table 1, indicating that our treatments explain a much smaller part of the variation in estimated loss aversion. A likely reason is that our estimates of loss aversion are imprecise, since they are identified from six problems only.

In the most extreme pull treatment (Pull = 2), the mean $\hat{\lambda}$ is 1.10 with a standard error of 0.086, which is not statistically distinguishable from 1 (p-value of 0.12; one-sided t-test). Moreover,

[19] Though T&K estimate λ to be 2.25, there is still no consensus about the value of λ in the literature, and some researchers even dispute the existence of loss aversion (e.g., Ert and Erev, 2010). Among the papers reviewed by Abdellaoui, Bleichrodt, and Paraschiv (2007, Tables 1 and 5), the range of loss aversion estimates is $\hat{\lambda} \in [0.74, 8.27]$, and among the papers reviewed by Booij, van Praag, and Kuilen (2010, Table 1), the range is $\hat{\lambda} \in [1.07, 2.61]$.

when Pull = 2, almost half (42%) of participants actually exhibit *loss seeking* behavior! Thus our framing manipulation can nearly drive out loss aversion.

Hypothesis 4 predicts that displaying the expected value of the prospects will cause $\hat{\lambda}$ to become closer to 1. Figure 7 shows mean $\hat{\lambda}$ by expected value treatment. Displaying the expected value does not appear to affect estimated loss aversion. Table 2 confirms the point estimates of essentially zero in regressions of estimated loss aversion on the expected-value-treatment dummy. Overall, Hypothesis 4 is not supported by our data.

4.3 Framing and the Other CPT Parameters

Although we have focused on the three parameters, $\hat{\gamma}^+$, $\hat{\gamma}^-$, and $\hat{\lambda}$, for which we had formulated *ex ante* hypotheses, our baseline MLE specification estimated five other parameters as well: $\hat{\alpha}^+$, $\hat{\alpha}^-$, $\hat{\beta}^+$, $\hat{\beta}^-$, and $\hat{\sigma}$. We are cautious about interpreting the framing effects we find for these other five parameters because ten additional tests raises multiple hypothesis testing concerns. We quickly summarize these findings only for completeness. We report the detailed results in Online Appendix II. Because the empirical distributions of these five parameters appear to be lognormal, our regression analyses are conducted using logarithms of the ML estimates.

The mean values of the probability weighting function parameters, $\hat{\alpha}^+$, $\hat{\alpha}^-$, $\hat{\beta}^+$, and $\hat{\beta}^-$, are in accord with findings from prior work.[20] The parameters that regulate curvature, $\hat{\alpha}^+$ and $\hat{\alpha}^-$, are decreasing in Pull and increasing in the EV treatment dummy. The treatment effects on $\hat{\beta}^+$ and $\hat{\beta}^-$, which determine elevation, are less consistent: $\hat{\beta}^-$ (but not $\hat{\beta}^+$) is increasing in Pull, and $\hat{\beta}^+$ (but not $\hat{\beta}^-$) is increasing in the EV treatment dummy. The estimated standard deviation of the choice noise, $\hat{\sigma}$, is decreasing in Pull and in the EV treatment dummy.

[20] We find mean values of $\hat{\alpha}^+ = 0.65$, $\hat{\alpha}^- = 0.76$, $\hat{\beta}^+ = 1.09$, and $\hat{\beta}^- = 1.03$. Booij, van Praag, and Kuilen's (2010) Table 1 only lists three studies that estimated the two-parameter Prelec (1998) functional form, and they only did so for prospects in the gain domain. The ranges of estimates are $\hat{\alpha}^+ \in [0.53, 1.05]$ and $\hat{\beta}^+ \in [1.08, 2.12]$. Hence our $\hat{\beta}^+$ estimate coincides with the bottom of the range. Since $\hat{\beta}^+$ and $\hat{\beta}^-$ are both approximately 1, our $\hat{\alpha}^+$ and $\hat{\alpha}^-$ parameter estimates are closely comparable with those estimated from the one-parameter Prelec functional form (which is the special case of the two-parameter Prelec (1998) functional form where $\beta^+ = \beta^- = 1$). The ranges of estimates for studies that estimated the one-parameter Prelec functional form are $\hat{\alpha}^+ \in [0.53, 1.00]$ and $\hat{\alpha}^- \in [0.41, 0.77]$.

4.4 Robustness to Other Probability Weighting Functions

To test the robustness of our results to the assumed probability weighting functional form, we also estimate our model with the identity function, $\omega(p) = p$; the one-parameter function used by T&K, $\omega(p) = p^\alpha/(p^\alpha + (1-p)^\alpha)^{\frac{1}{\alpha}}$; and the two-parameter function suggested by Goldstein and Einhorn (1987) and Lattimore, Baker, and Witte (1992), $\beta p^\alpha/(\beta p^\alpha + (1-p)^\alpha)$.[21] (For simplicity and to reduce the number of subjects for whom the MLE does not converge, we run those robustness checks separately for Parts A and B.) We find that the positive correlation between Pull and $\hat{\gamma}^+$ and $\hat{\gamma}^-$ is robust across these alternative specifications. Moreover, the expected value treatment has no significant effect on $\hat{\gamma}^+$ or $\hat{\gamma}^-$ in any of these alternative specifications, thus reinforcing our conclusions that our data provides no support for Hypothesis 3. Details are in Online Appendix III.

5 Conclusion

We tested whether choices over risky prospects, and the resulting preference parameter estimates, are affected by framing effects that are implicitly introduced by the experimenter. Our experimental results indicate that elicited risk preferences are sensitive to scale effects but insensitive to information about expected value. The finding that elicited risk preferences are sensitive to scale effects has two cautionary implications. First, economists should not expect risk aversion measures to be similar across experiments – or across experiments and risky-choice settings in the field – since elicitation methods tend to vary. Second, risk aversion measurements need to be interpreted jointly with the scales that were used to obtain those measures.

Our findings raise three questions for further research. First, these results beg the question of why scale-based framing effects are so much more influential than expected-value framing effects. We speculate that expected value is a concept that most decision-makers already take into account without any help from experimenters, and consequently providing this "redundant" information in an experiment does little, if anything, to change subjects' choices. On the other hand, understanding how to trade off risk and return is much harder for most people, and implicit suggestions about how

[21] Gonzalez and Wu (1999) note that it is difficult to empirically distinguish this latter function from the Prelec function we use in our baseline specification.

to make such tradeoffs – suggestions that are introduced by scale manipulations – are impactful. Future work should explore these hypotheses.

Second, given that elicited risk preferences are sensitive to the scale of the response options, which scales should researchers use? One approach would posit that external validity is the ultimate criterion for judging a preference measurement technique. From that point of view, a researcher should test which types of scales generate laboratory measures of risk aversion and loss aversion that correspond most closely with risk-related behavior outside of the lab. We do not have a strong view about which approach should be used, but we do believe that economists need to think about this question and develop an explicit framework for picking among experimental frames.

Third, could a version of prospect theory in which the reference point reflects a participant's expectations explain why the scale manipulations influence risky behavior? As in Tversky and Kahneman (1992), our estimation of the prospect theory parameters has assumed that the reference point is the participant's status quo wealth. Köszegi and Rabin (2006, 2007) have argued that the assumption that the reference point is the participant's (possibly stochastic) expectation of wealth provides a better explanation of risk-taking behavior in a variety of contexts. Nonetheless, analyses of experiments like ours, which use a multiple price list elicitation, have generally continued to assume a status quo reference point because it is not clear how to model a participant's expectations (which are presumably changing throughout the experiment). One possibility is that the fixed prospect in the price list pins down a participant's expectation (e.g., Sprenger, 2011). Since the fixed prospect was held constant across our scale manipulations, the scale effects we find could not be explained by a version of prospect theory with this model of reference point formation.

Finally, our work joins a growing body of research that casts doubt on the strength of loss aversion (cf. Wakker 2010). In general, we find very little loss aversion, and our most extreme framing manipulation is strong enough to make loss aversion effectively vanish altogether.

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Table 1: Regressions of ML Estimates of γ^+ and γ^- on Pull and Expected Value Treatments

	Gain Domain: $\hat{\gamma}^+$			Loss Domain: $\hat{\gamma}^-$		
Expected value dummy	0.015	0.014	0.025	-0.036*	-0.037*	-0.026
	(0.016)	(0.016)	(0.017)	(0.018)	(0.018)	(0.019)
Linear pull variable	-	0.038***	-	-	0.041***	-
		(0.006)			(0.006)	
Pull -2 dummy	-0.082***	-	-	-0.094***	-	-
	(0.025)			(0.028)		
Pull -1 dummy	-0.047†	-	-	-0.032	-	-
	(0.27)			(0.030)		
Pull 1 dummy	0.058*	-	-	0.056†	-	-
	(0.026)			(0.029)		
Pull 2 dummy	0.58*	-	-	0.067*	-	-
	(0.025)			(0.028)		
Constant	0.327***	0.325***	0.320***	0.333***	0.332***	0.327***
	(0.021)	(0.011)	(0.012)	(0.023)	(0.006)	(0.013)
F-stat for 4 Pull dummies	12.57	-	-	11.58	-	-
F-stat p-value	$< .0001$	-	-	$< .0001$	-	-
Observations	460	460	460	462	462	462
R-Squared	0.104	0.099	0.002	0.096	0.093	0.004

NOTE: The F-tests in the first and fourth specifications are for the joint significance of the four Pull dummies.

† Significant at 10% level; * significant at 5% level; ** significant at 1% level; *** significant at 0.1% level.

Table 2: Regressions of ML Estimates of Loss Aversion λ on Pull and Expected Value Treatments

	Estimated Loss Aversion $\hat{\lambda}$		
Expected value dummy	0.022	0.021	-0.001
	(0.087)	(0.086)	(0.086)
Linear pull variable	-	-0.074*	-
		(0.030)	
Pull -2 dummy	0.153	-	-
	(0.136)		
Pull -1 dummy	0.124	-	-
	(0.143)		
Pull 1 dummy	-0.052	-	-
	(0.140)		
Pull 2 dummy	-0.131	-	-
	(0.136)		
Constant	1.219***	1.24***	1.248***
	(0.112)	(0.062)	(0.062)
F-stat for 4 Pull dummies	1.59	-	-
F-stat p-value	0.1771	-	-
Observations	440	440	440
R-Squared	0.014	0.014	0.000

NOTE: The F-tests in the first specification is for the joint significance of the Pull dummies.
† Significant at 10% level; * significant at 5% level; ** significant at 1% level; *** significant at 0.1% level.

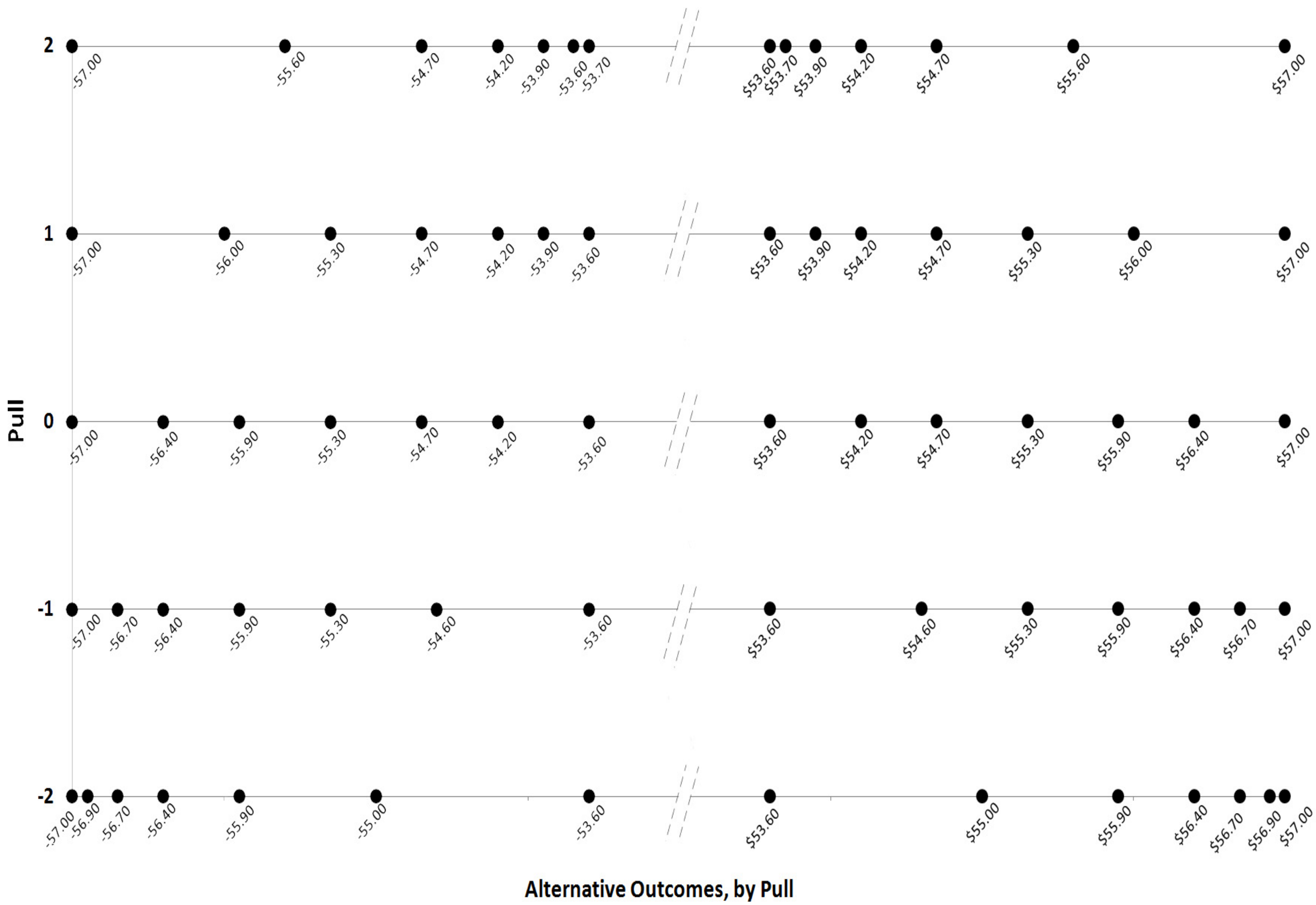

Figure 1. Alternative Outcomes by Pull Treatment, for Example Screen from Part A with Fixed Prospect Offering a 10% Chance of Gaining $100 and a 90% Chance of Gaining $50

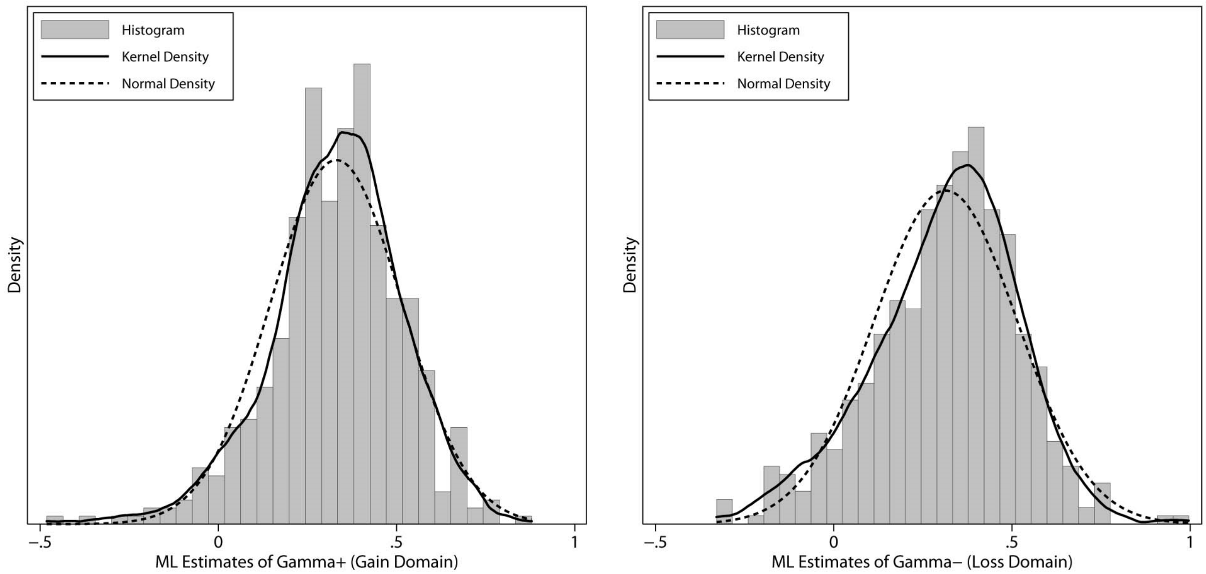

Figure 2. Distribution of ML Estimates of γ^+ and γ^-

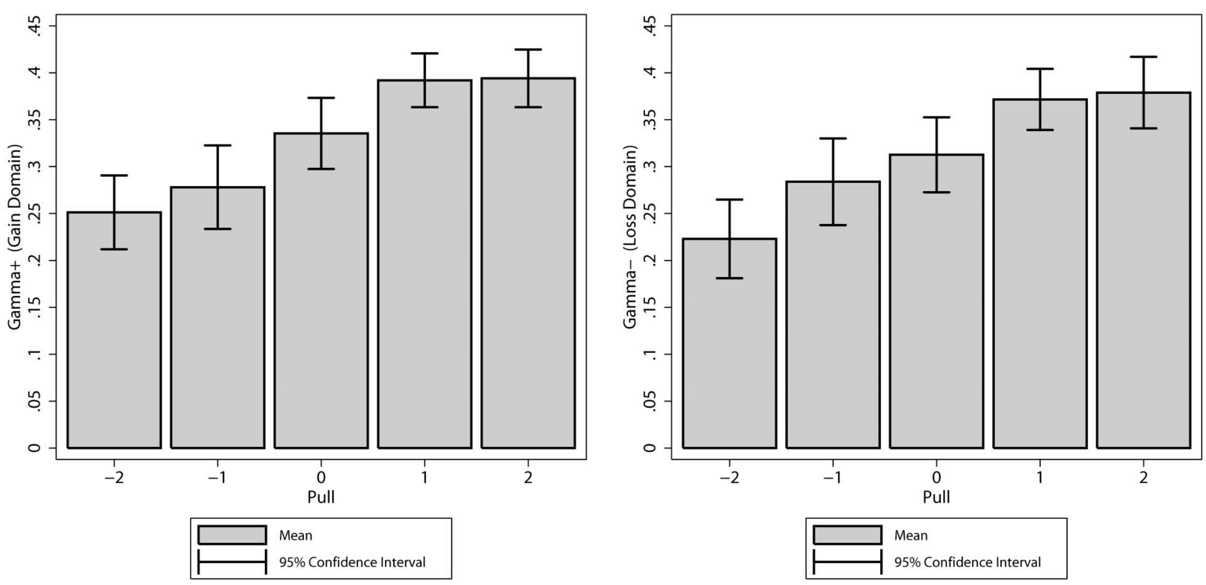

Figure 3. Mean ML Estimates of γ^+ and γ^- by Pull Treatment, with 95% Confidence Intervals

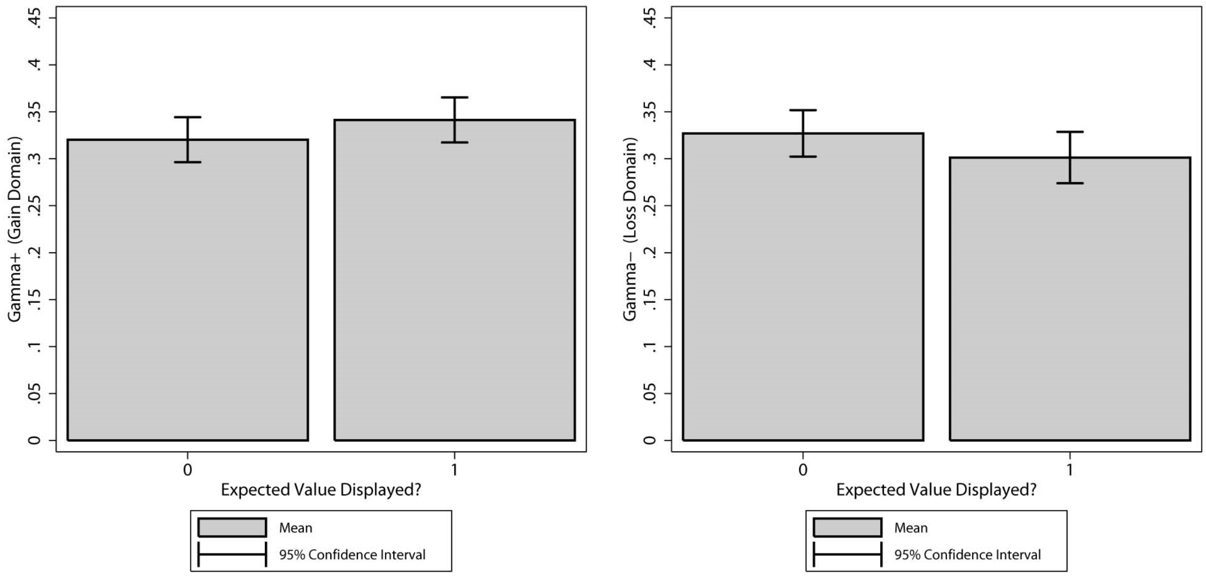

Figure 4. Mean ML Estimates of γ^+ and γ^- by Expected Value Treatment, with 95% Confidence Intervals

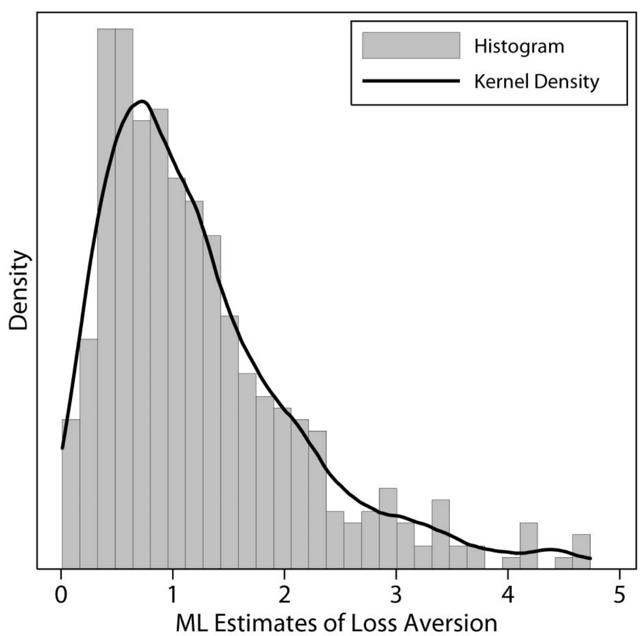

Figure 5. Distribution of ML Estimates of Loss Aversion λ

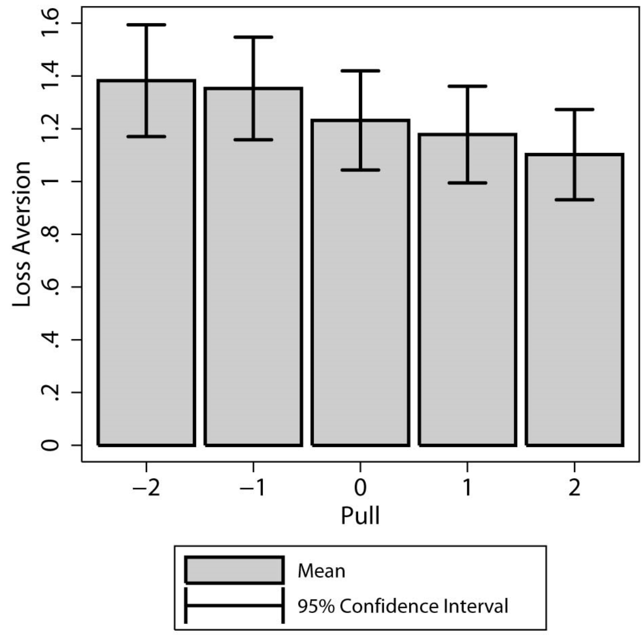

Figure 6. Mean ML Estimates of Loss Aversion λ by Pull Treatment, with 95% Confidence Intervals

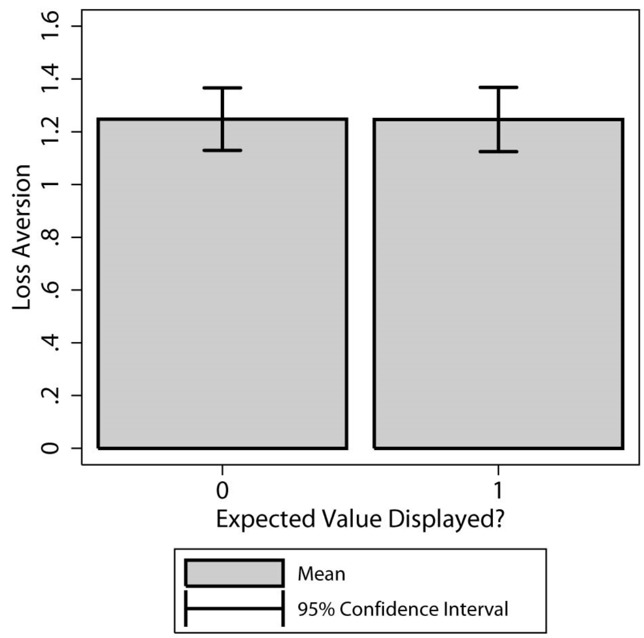

Figure 7. Mean ML Estimates of Loss Aversion λ by Expected Value Treatment, with 95% Confidence Intervals

7 APPENDIX: Screenshots of the Experiment

Screen shots of a randomly selected screen from each part of the experiment, for a participant in the Pull -1 and EV treatments, are shown below. Each scenario appears on a separate screen in the experiment.

This study consists of a total of 64 scenarios, divided into four parts. You have completed 7 of the 64 scenarios.

Part A: Scenario 8 of 28

For each of questions (a) to (g), please mark your preferred option.

A gamble gives you a 75% chance of gaining $200 and a 25% chance of gaining $100 instead.

On average, you would gain $175 from taking this gamble.

Would you rather...

(a) Take the gamble (gain $175 on average) OR Gain $180.30
(b) Take the gamble (gain $175 on average) OR Gain $179.30
(c) Take the gamble (gain $175 on average) OR Gain $178.00
(d) Take the gamble (gain $175 on average) OR Gain $176.40
(e) Take the gamble (gain $175 on average) OR Gain $174.30
(f) Take the gamble (gain $175 on average) OR Gain $171.60
(g) Take the gamble (gain $175 on average) OR Gain $168.30

Continue Clear

This study consists of a total of 64 scenarios, divided into four parts. You have completed 44 of the 64 scenarios.

Part B: Scenario 17 of 28

For each of questions (a) to (g), please mark your preferred option.

A gamble gives you a 50% chance of losing $150 and a 50% chance of losing $50 instead.

On average, you would lose $100 from taking this gamble.

Would you rather...

(a) Take the gamble (lose $100 on average) OR Lose $86.70
(b) Take the gamble (lose $100 on average) OR Lose $93.80
(c) Take the gamble (lose $100 on average) OR Lose $99.30
(d) Take the gamble (lose $100 on average) OR Lose $103.70
(e) Take the gamble (lose $100 on average) OR Lose $107.10
(f) Take the gamble (lose $100 on average) OR Lose $109.70
(g) Take the gamble (lose $100 on average) OR Lose $111.80

Continue Clear

This study consists of a total of 64 scenarios, divided into four parts. You have completed 56 of the 64 scenarios.

Part C: Scenario 1 of 4

For each of questions (a) to (g), please mark your preferred option.

A gamble gives you a 50% chance of losing $50 and ...

(a)	... a 50% chance of gaining $0.00 instead.	Take the gamble (lose $25.00 on average)	OR	Don't take the gamble
(b)	... a 50% chance of gaining $42.30 instead.	Take the gamble (lose $3.85 on average)	OR	Don't take the gamble
(c)	... a 50% chance of gaining $75.40 instead.	Take the gamble (gain $12.70 on average)	OR	Don't take the gamble
(d)	... a 50% chance of gaining $101.30 instead.	Take the gamble (gain $25.65 on average)	OR	Don't take the gamble
(e)	... a 50% chance of gaining $121.60 instead.	Take the gamble (gain $35.80 on average)	OR	Don't take the gamble
(f)	... a 50% chance of gaining $137.50 instead.	Take the gamble (gain $43.75 on average)	OR	Don't take the gamble
(g)	... a 50% chance of gaining $150.00 instead.	Take the gamble (gain $50.00 on average)	OR	Don't take the gamble

Continue Clear

This study consists of a total of 64 scenarios, divided into four parts. You have completed 62 of the 64 scenarios.

Part D: Scenario 3 of 4

For each of questions (a) to (g), please mark your preferred option.

Gamble 1 gives you a 50% chance of losing $50 and a 50% chance of gaining $150.

Gamble 2 gives you a 50% chance of losing $125 and ...

(a)	... a 50% chance of gaining $375.00 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $125.00 on average)
(b)	... a 50% chance of gaining $356.30 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $115.65 on average)
(c)	... a 50% chance of gaining $332.50 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $103.75 on average)
(d)	... a 50% chance of gaining $302.00 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $88.50 on average)
(e)	... a 50% chance of gaining $263.10 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $69.05 on average)
(f)	... a 50% chance of gaining $213.40 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $44.20 on average)
(g)	... a 50% chance of gaining $150.00 instead.	Take gamble 1 (gain $50 on average)	OR	Take gamble 2 (gain $12.50 on average)

Continue Clear

ONLINE APPENDIX I

Below, we list the complete set of fixed prospects and alternative outcomes faced by the participants in the experiment, for each Pull treatment. Online Appendix Table I lists the fixed prospects and alternative outcomes for Part A (Part B is identical to Part A but with all amounts multiplied by -1); Online Appendix Table II lists the fixed prospects and the unfixed parts of the alternative prospects for Parts C and D.

Online Appendix Table I: Fixed Prospects and Alternative Outcomes for Part A, by Pull Treatment

	#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
Fixed Prospects	x_l	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	50	50	50	50	50	50	50	100	100	100	100	100
	x_h	50	50	50	100	100	100	100	100	200	200	200	200	200	400	400	100	100	100	150	150	150	150	150	200	200	200	200	200
	$P(x_l)$	0.90	0.50	0.10	0.95	0.75	0.50	0.25	0.05	0.99	0.90	0.50	0.10	0.01	0.99	0.01	0.90	0.50	0.10	0.95	0.75	0.50	0.25	0.05	0.95	0.75	0.50	0.25	0.05
	$P(x_h)$	0.10	0.50	0.90	0.05	0.25	0.50	0.75	0.95	0.01	0.10	0.50	0.90	0.99	0.01	0.99	0.10	0.50	0.90	0.05	0.25	0.50	0.75	0.95	0.05	0.25	0.50	0.75	0.95
Alternative Sure Outcomes	Pull 2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	73.2	0.0	146.4	53.6	70.8	93.3	52.8	65.9	86.7	114.1	142.0	103.5	119.0	141.5	168.3	193.2
		0.5	1.2	1.6	0.7	1.7	2.3	2.9	3.8	0.7	2.1	4.7	6.3	77.4	1.3	154.7	53.7	71.0	93.4	53.0	66.6	87.6	114.7	142.2	103.7	119.4	142.1	168.7	193.3
		1.4	3.1	4.2	2.0	4.4	6.2	7.6	9.1	1.8	5.6	12.4	16.7	84.3	3.5	168.5	53.9	71.5	93.6	53.4	67.7	88.9	115.7	142.4	103.9	120.1	143.0	169.3	193.5
		2.8	6.3	8.5	4.0	9.0	12.7	15.5	17.9	3.6	11.3	25.3	34.0	95.7	7.2	191.5	54.2	72.2	93.8	54.0	69.6	91.2	117.4	142.8	104.2	121.4	144.5	170.4	193.7
		5.2	11.7	15.7	7.4	16.5	23.4	28.6	32.6	6.6	20.9	46.8	62.7	114.8	13.2	229.6	54.7	73.5	94.3	54.9	72.7	95.0	120.1	143.5	104.8	123.4	147.0	172.2	194.2
		9.2	20.6	27.6	13.0	29.1	41.2	50.4	57.0	11.6	36.8	82.3	110.5	146.4	23.3	292.9	55.6	75.6	95.0	56.5	77.9	101.3	124.7	144.7	105.7	126.7	151.2	175.3	195.0
		15.8	35.4	47.4	22.4	50.0	70.7	86.6	97.5	20.0	63.2	141.4	189.7	199.0	40.0	398.0	57.0	79.1	96.2	59.2	86.6	111.8	132.3	146.6	107.2	132.3	158.1	180.3	196.2
	Pull 1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	73.2	0.0	146.4	53.6	70.8	93.3	52.8	65.9	86.7	114.1	142.0	103.5	119.0	141.5	168.3	193.2
		1.3	2.9	3.9	1.9	4.2	5.9	7.2	8.6	1.7	5.3	11.7	15.8	83.7	3.3	167.3	53.9	71.4	93.6	53.4	67.6	88.8	115.6	142.4	103.8	120.1	142.9	169.3	193.5
		3.0	6.7	9.0	4.2	9.5	13.4	16.4	18.9	3.8	12.0	26.7	35.9	97.0	7.6	194.0	54.2	72.3	93.9	54.0	69.8	91.5	117.5	142.9	104.2	121.5	144.6	170.5	193.8
		5.1	11.5	15.4	7.3	16.2	22.9	28.1	32.0	6.5	20.5	45.9	61.6	114.0	13.0	228.1	54.7	73.4	94.2	54.9	72.6	94.9	120.0	143.5	104.7	123.3	146.9	172.2	194.2
		7.9	17.6	23.6	11.1	24.9	35.2	43.1	48.8	9.9	31.5	70.3	94.4	135.8	19.9	271.5	55.3	74.9	94.7	56.0	76.2	99.2	123.1	144.3	105.4	125.6	149.8	174.2	194.7
		11.4	25.4	34.1	16.1	35.9	50.8	62.2	70.2	14.4	45.4	101.6	136.3	163.5	28.7	327.1	56.0	76.7	95.4	57.4	80.8	104.7	127.2	145.3	106.2	128.5	153.4	176.9	195.4
		15.8	35.4	47.4	22.4	50.0	70.7	86.6	97.5	20.0	63.2	141.4	189.7	199.0	40.0	398.0	57.0	79.1	96.2	59.2	86.6	111.8	132.3	146.6	107.2	132.3	158.1	180.3	196.2
	Pull 0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	73.2	0.0	146.4	53.6	70.8	93.3	52.8	65.9	86.7	114.1	142.0	103.5	119.0	141.5	168.3	193.2
		2.6	5.9	7.9	3.7	8.3	11.8	14.4	16.7	3.3	10.5	23.6	31.6	94.2	6.7	188.3	54.2	72.1	93.8	53.9	69.3	90.9	117.1	142.8	104.2	121.2	144.3	170.3	193.7
		5.3	11.8	15.8	7.5	16.7	23.6	28.9	32.9	6.7	21.1	47.1	63.2	115.1	13.3	230.3	54.7	73.5	94.3	54.9	72.8	95.1	120.2	143.6	104.8	123.4	147.0	172.3	194.2
		7.9	17.7	23.7	11.2	25.0	35.4	43.3	49.0	10.0	31.6	70.7	94.9	136.1	20.0	272.2	55.3	74.9	94.8	56.0	76.2	99.3	123.2	144.3	105.4	125.6	149.8	174.3	194.7
		10.5	23.6	31.6	14.9	33.3	47.1	57.7	65.2	13.3	42.2	94.3	126.5	157.1	26.7	314.1	55.9	76.3	95.2	57.1	79.7	103.4	126.2	145.1	106.0	127.8	152.6	176.3	195.2
		13.2	29.5	39.5	18.6	41.7	58.9	72.2	81.3	16.7	52.7	117.9	158.1	178.0	33.3	356.1	56.4	77.7	95.7	58.1	83.1	107.6	129.3	145.9	106.6	130.1	155.3	178.3	195.7
		15.8	35.4	47.4	22.4	50.0	70.7	86.6	97.5	20.0	63.2	141.4	189.7	199.0	40.0	398.0	57.0	79.1	96.2	59.2	86.6	111.8	132.3	146.6	107.2	132.3	158.1	180.3	196.2
	Pull -1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	73.2	0.0	146.4	53.6	70.8	93.3	52.8	65.9	86.7	114.1	142.0	103.5	119.0	141.5	168.3	193.2
		4.5	10.0	13.4	6.3	14.1	19.9	24.4	27.9	5.6	17.8	39.9	53.5	108.7	11.3	217.3	54.6	73.1	94.1	54.6	71.7	93.8	119.2	143.3	104.6	122.7	146.2	171.6	194.1
		7.9	17.8	23.8	11.2	25.1	35.5	43.5	49.3	10.1	31.8	71.1	95.4	136.4	20.1	272.9	55.3	74.9	94.8	56.0	76.3	99.3	123.2	144.3	105.4	125.7	149.9	174.3	194.7
		10.7	23.9	32.0	15.1	33.8	47.8	58.5	66.0	13.5	42.7	95.5	128.2	158.2	27.0	316.4	55.9	76.4	95.3	57.1	79.9	103.7	126.4	145.1	106.0	128.0	152.7	176.4	195.2
		12.8	28.7	38.5	18.1	40.5	57.3	70.2	79.1	16.2	51.3	114.7	153.9	175.2	32.4	350.4	56.4	77.5	95.6	58.0	82.7	107.1	128.8	145.8	106.5	129.8	155.0	178.0	195.6
		14.5	32.4	43.5	20.5	45.8	64.8	79.4	89.4	18.3	58.0	129.7	174.0	188.6	36.7	377.1	56.7	78.4	95.9	58.6	84.9	109.7	130.8	146.2	106.9	131.2	156.7	179.3	196.0
		15.8	35.4	47.4	22.4	50.0	70.7	86.6	97.5	20.0	63.2	141.4	189.7	199.0	40.0	398.0	57.0	79.1	96.2	59.2	86.6	111.8	132.3	146.6	107.2	132.3	158.1	180.3	196.2
	Pull -2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	73.2	0.0	146.4	53.6	70.8	93.3	52.8	65.9	86.7	114.1	142.0	103.5	119.0	141.5	168.3	193.2
		6.6	14.8	19.8	9.3	20.9	29.5	36.2	41.1	8.4	26.4	59.1	79.3	125.8	16.7	251.5	55.0	74.2	94.5	55.5	74.5	97.2	121.7	143.9	105.1	124.5	148.4	173.3	194.5
		10.6	23.7	31.8	15.0	33.5	47.3	58.0	65.4	13.4	42.3	94.7	127.0	157.4	26.8	314.8	55.9	76.3	95.2	57.1	79.8	103.5	126.3	145.1	106.0	127.9	152.6	176.3	195.2
		13.0	29.0	38.9	18.4	41.0	58.0	71.1	80.1	16.4	51.9	116.1	155.8	176.5	32.8	352.9	56.4	77.6	95.7	58.0	82.9	107.3	129.0	145.8	106.6	129.9	155.1	178.1	195.7
		14.4	32.2	43.3	20.4	45.6	64.5	79.0	88.9	18.2	57.7	129.0	173.1	187.9	36.5	375.9	56.7	78.3	95.9	58.6	84.8	109.6	130.7	146.2	106.9	131.1	156.7	179.2	195.9
		15.3	34.2	45.9	21.6	48.3	68.4	83.7	94.3	19.3	61.2	136.7	183.5	194.8	38.7	389.7	56.9	78.8	96.1	59.0	85.9	111.0	131.7	146.5	107.1	131.8	157.6	179.9	196.1
		15.8	35.4	47.4	22.4	50.0	70.7	86.6	97.5	20.0	63.2	141.4	189.7	199.0	40.0	398.0	57.0	79.1	96.2	59.2	86.6	111.8	132.3	146.6	107.2	132.3	158.1	180.3	196.2

NOTES: Part A consists of 28 problems. Each problem appears on a separate screen and involves choices between a fixed prospect (x_l, $P(x_l)$; x_h, $P(x_h)$) and seven alternative sure outcomes. The different Pull treatments vary the second through sixth alternative sure outcomes presented with each fixed prospect on each screen.

Online Appendix Table II: Fixed Prospects and Unfixed Parts of the Alternative Prospects for Parts C and D, by Pull Treatment

	Problem #		1	2	3	4	5	6	7	8
Fixed Prospects	x_1		0	0	0	0	-20	-50	50	100
	x_2		0	0	0	0	50	150	120	300
Alternative Prospects	y_1		-25	-50	-100	-150	-50	-125	20	25
	y_2	Pull 2	0	0	0	0	50	150	120	300
			2	5	10	15	53	157	123	307
			7	13	26	40	58	170	128	320
			13	27	54	81	66	190	136	340
			25	50	99	149	80	224	150	374
			44	87	175	262	102	281	172	431
			75	150	300	450	140	375	210	525
		Pull 1	0	0	0	0	50	150	120	300
			6	12	25	37	57	169	127	319
			14	28	57	85	67	193	137	343
			24	49	97	146	79	223	149	373
			37	75	149	224	95	262	165	412
			54	108	215	323	115	312	185	462
			75	150	300	450	140	375	210	525
		Pull 0	0	0	0	0	50	150	120	300
			13	25	50	75	65	188	135	338
			25	50	100	150	80	225	150	375
			38	75	150	225	95	263	165	413
			50	100	200	300	110	300	180	450
			63	125	250	375	125	338	195	488
			75	150	300	450	140	375	210	525
		Pull -1	0	0	0	0	50	150	120	300
			21	42	85	127	75	213	145	363
			38	75	151	226	95	263	165	413
			51	101	203	304	111	302	181	452
			61	122	243	365	123	332	193	482
			69	138	275	413	133	356	203	506
			75	150	300	450	140	375	210	525
		Pull -2	0	0	0	0	50	150	120	300
			31	63	125	188	88	244	158	394
			50	100	201	301	110	301	180	451
			62	123	246	369	124	335	194	485
			68	137	274	410	132	355	202	505
			73	145	290	435	137	368	207	518
			75	150	300	450	140	375	210	525

NOTES: Part C consists of Problems 1-4; Part D consists of Problems 5-8. Each problem appears on a separate screen and involves choices between a fixed prospect (x_1, 0.50; x_2, 0.50) and seven alternative prospects (y_1, 0.50; y_2, 0.50). For each problem, y_1 is fixed and y_2 is unfixed. The different Pull treatments vary the unfixed part (y_2) of the second through sixth alternative prospects on each screen.

ONLINE APPENDIX II
Effects of the Pull and Expected Value Treatments on the Five Other Estimated CPT Parameters (α^+, α^-, β^+, β^-, and σ)

Below, we report the results of our analyses of the framing effects for the five other estimated Cumulative Prospect Theory parameters (for which we had not formulated *ex ante* hypotheses): α^+, α^-, β^+, β^-, and σ. Because the empirical distributions of these five parameters are manifestly lognormal, our regression analyses are conducted using logarithms of the ML estimates. Negative estimates are dropped.

Analyses for log(α^+)

Looking at the data after dropping the outliers:

```
. sum logAlphaGain

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
logAlphaGain |       453   -.5777571     .5419594  -2.209985   1.425557


. inspect logAlphaGain

logAlphaGain:                                   Number of Observations
---------------                             ------------------------------
                                            Total   Integers   Nonintegers
|          #                Negative          411          -           411
|          #                Zero                -          -             -
|          #                Positive           42          -            42
|      #   #                                -----      -----         -----
|      #   #                Total             453          -           453
|  .   #   #   .   .        Missing             -
+----------------------                     -----
-2.209985      1.425557                       453
(More than 99 unique values)
```

Regressing log(α^+) on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
. reg logAlphaGain dum_*

      Source |       SS       df       MS              Number of obs =     453
-------------+------------------------------           F(  5,   447) =    5.79
       Model |  8.08004933     5  1.61600987           Prob > F      =  0.0000
    Residual |  124.681372   447  .278929245           R-squared     =  0.0609
-------------+------------------------------           Adj R-squared =  0.0504
       Total |  132.761422   452   .29371996           Root MSE      =  .52814

------------------------------------------------------------------------------
logAlphaGain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dum_PullMi~2 |    .164217   .0787564     2.09   0.038     .0094382    .3189958
dum_PullMi~1 |  -.0596369   .0826255    -0.72   0.471    -.2220197    .1027458
   dum_Pull1 |  -.0883836   .0815974    -1.08   0.279    -.2487457    .0719786
   dum_Pull2 |  -.1196666   .0783557    -1.53   0.127    -.2736579    .0343247
      dum_EV |   .1826728   .0500329     3.65   0.000     .0843438    .2810017
       _cons |  -.6530024   .0647252   -10.09   0.000    -.7802058    -.525799
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies :

```
. test dum_PullMinus2 dum_PullMinus1 dum_Pull1 dum_Pull2

 ( 1)  dum_PullMinus2 = 0
 ( 2)  dum_PullMinus1 = 0
 ( 3)  dum_Pull1 = 0
 ( 4)  dum_Pull2 = 0

       F(  4,   447) =    4.45
            Prob > F =    0.0015
```

Regressing log(α^+) on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
. reg logAlphaGain Pull dum_EV

      Source |       SS       df       MS              Number of obs =     453
-------------+------------------------------           F(  2,   450) =   12.10
       Model |  6.77470016     2  3.38735008           Prob > F      =  0.0000
    Residual |  125.986722   450  .279970493           R-squared     =  0.0510
-------------+------------------------------           Adj R-squared =  0.0468
       Total |  132.761422   452   .29371996           Root MSE      =  .52912

------------------------------------------------------------------------------
logAlphaGain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |  -.0614936   .0169967    -3.62   0.000    -.0948963   -.0280909
      dum_EV |   .1847257   .0500064     3.69   0.000     .0864506    .2830008
       _cons |  -.6711405   .0355968   -18.85   0.000    -.7410971    -.601184
------------------------------------------------------------------------------
```

Analyses for log(α^-)

Looking at the data after dropping the outliers:

```
. sum logAlphaLoss

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
logAlphaLoss |       454   -.4112313     .502356  -2.128252   1.427697


. inspect logAlphaLoss

logAlphaLoss:                                   Number of Observations
---------------                              ------------------------------
                                             Total   Integers   Nonintegers
|          #                 Negative          379          -           379
|          #                 Zero                -          -             -
|          #                 Positive           75          -            75
|          #                                 -----      -----         -----
|      #   #                 Total             454          -           454
|  .   #   #   #   .         Missing             -
+----------------------                      -----
-2.128252      1.427697                        454
(More than 99 unique values)
```

Regressing log(α⁻) on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
. reg logAlphaLoss dum_*

      Source |       SS       df       MS              Number of obs =     454
-------------+------------------------------           F(  5,   448) =    5.30
       Model |  6.38113822     5  1.27622764           Prob > F      =  0.0001
    Residual |  107.938641   448  .240934466           R-squared     =  0.0558
-------------+------------------------------           Adj R-squared =  0.0453
       Total |  114.319779   453  .252361543           Root MSE      =  .49085

------------------------------------------------------------------------------
logAlphaLoss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dum_PullMi~2 |   .1862027   .0735175     2.53   0.012     .0417207    .3306848
dum_PullMi~1 |  -.1043601   .0765865    -1.36   0.174    -.2548736    .0461533
   dum_Pull1 |  -.0389878   .0749715    -0.52   0.603    -.1863273    .1083517
   dum_Pull2 |  -.1002874   .0718675    -1.40   0.164    -.2415268     .040952
      dum_EV |   .1082361   .0464047     2.33   0.020     .0170381     .199434
       _cons |  -.4563056   .0595183    -7.67   0.000    -.5732752   -.3393359
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies :

```
. test dum_PullMinus2 dum_PullMinus1 dum_Pull1 dum_Pull2

 ( 1)  dum_PullMinus2 = 0
 ( 2)  dum_PullMinus1 = 0
 ( 3)  dum_Pull1 = 0
 ( 4)  dum_Pull2 = 0

       F(  4,   448) =    5.54
            Prob > F =    0.0002
```

Regressing log(α⁻) on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
. reg logAlphaLoss Pull dum_EV

      Source |       SS       df       MS              Number of obs =     454
-------------+------------------------------           F(  2,   451) =    7.67
       Model |  3.76030448     2  1.88015224           Prob > F      =  0.0005
    Residual |  110.559474   451  .245142959           R-squared     =  0.0329
-------------+------------------------------           Adj R-squared =  0.0286
       Total |  114.319779   453  .252361543           Root MSE      =  .49512

------------------------------------------------------------------------------
logAlphaLoss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |  -.0531013   .0159505    -3.33   0.001    -.0844478   -.0217548
      dum_EV |   .1100637   .0466759     2.36   0.019     .0183345     .201793
       _cons |  -.4643088   .0331806   -13.99   0.000    -.5295166    -.399101
------------------------------------------------------------------------------
```

Analyses for log(β^+)

Looking at the data after dropping the outliers:

```
. sum logBetaGain

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
 logBetaGain |       450   -.0075795    .4259549  -1.694164   1.694486

. inspect logBetaGain

logBetaGain:                                Number of Observations
--------------                             ------------------------------
                                            Total   Integers   Nonintegers
|          #                Negative          237          -           237
|          #                Zero                -          -             -
|          #                Positive          213          -           213
|          #                                -----      -----         -----
|          #                Total             450          -           450
|   .   #   #   #   .       Missing             -
+----------------------                     -----
-1.694164      1.694486                       450
(More than 99 unique values)
```

Regressing log(β^+) on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
. reg logBetaGain dum_*

      Source |       SS       df       MS              Number of obs =     450
-------------+------------------------------           F(  5,   444) =    1.98
       Model |  1.77880133     5  .355760266           Prob > F      =  0.0800
    Residual |   79.686668   444  .179474478           R-squared     =  0.0218
-------------+------------------------------           Adj R-squared =  0.0108
       Total |  81.4654694   449  .181437571           Root MSE      =  .42364

------------------------------------------------------------------------------
 logBetaGain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dum_PullMi~2 |  -.0338545   .0630733    -0.54   0.592    -.1578137    .0901048
dum_PullMi~1 |  -.0712431   .0660638    -1.08   0.281    -.2010797    .0585935
   dum_Pull1 |  -.0327982   .0656027    -0.50   0.617    -.1617285    .0961322
   dum_Pull2 |  -.0490222   .0627959    -0.78   0.435    -.1724363     .074392
      dum_EV |  -.1186445    .040266    -2.95   0.003      -.19778   -.0395089
       _cons |    .090955   .0515786     1.76   0.079    -.0104134    .1923235
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies :

```
. test dum_PullMinus2 dum_PullMinus1 dum_Pull1 dum_Pull2

 ( 1)  dum_PullMinus2 = 0
 ( 2)  dum_PullMinus1 = 0
 ( 3)  dum_Pull1 = 0
 ( 4)  dum_Pull2 = 0

       F(  4,   444) =    0.32
            Prob > F =    0.8676
```

Regressing log(β^+) on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
. reg logBetaGain Pull dum_EV

      Source |       SS       df       MS              Number of obs =     450
-------------+------------------------------           F(  2,   447) =    4.34
       Model |  1.55228039     2  .776140196           Prob > F      =  0.0136
    Residual |   79.913189   447  .178776709           R-squared     =  0.0191
-------------+------------------------------           Adj R-squared =  0.0147
       Total |  81.4654694   449  .181437571           Root MSE      =  .42282

------------------------------------------------------------------------------
 logBetaGain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0000677   .0136573     0.00   0.996    -.0267728    .0269083
      dum_EV |  -.1175284   .0401164    -2.93   0.004    -.1963686   -.0386882
       _cons |   .0527512   .0286501     1.84   0.066    -.0035544    .1090568
------------------------------------------------------------------------------
```

Analyses for log(β^-)

Looking at the data after dropping the outliers:

```
. sum logBetaLoss

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
 logBetaLoss |       450   -.0487822    .3849213  -1.354478   1.431973


. inspect logBetaLoss

logBetaLoss:                                 Number of Observations
--------------                              ------------------------------
                                            Total    Integers   Nonintegers
|          #                Negative          267           -           267
|          #                Zero                -           -             -
|          #                Positive          183           -           183
|          #                                -----       -----         -----
|          #                Total             450           -           450
|  .   #   #   .   .        Missing             -
+----------------------                     -----
-1.354478      1.431973                       450
(More than 99 unique values)
```

Regressing log(β^-) on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
. reg logBetaLoss dum_*

      Source |       SS       df       MS              Number of obs =     450
-------------+------------------------------           F(  5,   444) =    2.72
       Model |  1.98050516     5  .396101031           Prob > F      =  0.0194
    Residual |  64.5452981   444  .145372293           R-squared     =  0.0298
-------------+------------------------------           Adj R-squared =  0.0188
       Total |  66.5258032   449  .148164372           Root MSE      =  .38128

------------------------------------------------------------------------------
 logBetaLoss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dum_PullMi~2 |  -.1241756   .0570341    -2.18   0.030     -.236266   -.0120852
dum_PullMi~1 |  -.0238797    .059856    -0.40   0.690    -.1415159    .0937566
   dum_Pull1 |   .0063565   .0589384     0.11   0.914    -.1094764    .1221894
   dum_Pull2 |   .0600534   .0561233     1.07   0.285    -.0502468    .1703537
      dum_EV |   .0283956    .036203     0.78   0.433    -.0427549    .0995461
       _cons |  -.0470241    .046602    -1.01   0.313    -.1386119    .0445638
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies :

```
. test dum_PullMinus2 dum_PullMinus1 dum_Pull1 dum_Pull2

 ( 1)  dum_PullMinus2 = 0
 ( 2)  dum_PullMinus1 = 0
 ( 3)  dum_Pull1 = 0
 ( 4)  dum_Pull2 = 0

       F(  4,   444) =    3.10
            Prob > F =    0.0155
```

Regressing log(β^-) on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
. reg logBetaLoss Pull dum_EV

      Source |       SS       df       MS              Number of obs =     450
-------------+------------------------------           F(  2,   447) =    6.12
       Model |  1.77277019     2  .886385096           Prob > F      =  0.0024
    Residual |   64.753033   447  .144861371           R-squared     =  0.0266
-------------+------------------------------           Adj R-squared =  0.0223
       Total |  66.5258032   449  .148164372           Root MSE      =  .38061

------------------------------------------------------------------------------
 logBetaLoss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0406466   .0122508     3.32   0.001     .0165703     .064723
      dum_EV |   .0295484   .0360222     0.82   0.412    -.0412455    .1003424
       _cons |  -.0653546   .0256264    -2.55   0.011    -.1157177   -.0149915
------------------------------------------------------------------------------
```

Analyses for log(σ)

Looking at the data after dropping the outliers:

```
. sum logSigma

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
    logSigma |       461    .8301051    .9403862    -2.3047   4.411873

. inspect logSigma

logSigma:                                  Number of Observations
-----------                             ------------------------------
                                        Total   Integers   Nonintegers
|          #                  Negative     82          -            82
|          #                  Zero          -          -             -
|          #                  Positive    379          -           379
|      #   #                             -----     -----         -----
|      #   #                  Total       461          -           461
|  .   #   #   #   .          Missing       -
+----------------------                  -----
-2.3047        4.411873                    461
(More than 99 unique values)
```

Regressing log(σ) on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
. reg logSigma dum_*

      Source |       SS       df       MS              Number of obs =     461
-------------+------------------------------           F(  5,   455) =    8.85
       Model |  36.0407248     5  7.20814496           Prob > F      =  0.0000
    Residual |   370.74935   455  .814833735           R-squared     =  0.0886
-------------+------------------------------           Adj R-squared =  0.0786
       Total |  406.790074   460  .884326249           Root MSE      =  .90268

------------------------------------------------------------------------------
    logSigma |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dum_PullMi~2 |   .4730092   .1329071     3.56   0.000     .2118213    .7341972
dum_PullMi~1 |    .511722   .1403433     3.65   0.000     .2359204    .7875235
   dum_Pull1 |  -.0295306   .1370277    -0.22   0.829    -.2988163    .2397552
   dum_Pull2 |  -.0802057   .1320201    -0.61   0.544    -.3396505     .179239
      dum_EV |  -.1606569   .0846265    -1.90   0.058    -.3269641    .0056503
       _cons |   .7408793   .1085169     6.83   0.000     .5276229    .9541357
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies :

```
. test dum_PullMinus2 dum_PullMinus1 dum_Pull1 dum_Pull2

 ( 1)  dum_PullMinus2 = 0
 ( 2)  dum_PullMinus1 = 0
 ( 3)  dum_Pull1 = 0
 ( 4)  dum_Pull2 = 0

       F(  4,   455) =    9.54
            Prob > F =    0.0000
```

Regressing log(σ) on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
. reg logSigma Pull dum_EV

      Source |       SS       df       MS              Number of obs =     461
-------------+------------------------------           F(  2,   458) =   18.40
       Model |  30.2472582     2  15.1236291           Prob > F      =  0.0000
    Residual |  376.542816   458  .822145887           R-squared     =  0.0744
-------------+------------------------------           Adj R-squared =  0.0703
       Total |  406.790074   460  .884326249           Root MSE      =  .90672

------------------------------------------------------------------------------
    logSigma |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |  -.1601965   .0288848    -5.55   0.000    -.2169597   -.1034334
      dum_EV |  -.1644854   .0848249    -1.94   0.053    -.3311797     .002209
       _cons |   .9177666   .0602653    15.23   0.000     .7993357    1.036197
------------------------------------------------------------------------------
```

ONLINE APPENDIX III.A
Robustness of Main Results for γ^+, γ^- to Assumed Probability Weighting Function

To test the robustness of our results to the assumed probability weighting functional form, we also estimate our model with the identity function, w(p) = p; the one-parameter function used by T&K; and the two-parameter function suggested by Goldstein and Einhorn (1987) and Lattimore, Baker, and Witte (1992). (For simplicity and to reduce the number of subjects for whom the MLE does not converge, we estimate the model separately for γ^+ with the data from Part A and for γ^- with the data from Part B.) Results of these analyses are reported below.

Identity Probability Function (w(p)=p): Analyses for γ^+

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
  gamma_gain |       493    .3639346     .283744  -.7285563   .9898975
```

```
gamma_gain:                                          Number of Observations
--------                                        ------------------------------
                                                Total   Integers   Nonintegers
|              #             Negative              48          -            48
|              #             Zero                   -          -             -
|              #             Positive             445          -           445
|          #   #                                -----      -----         -----
|          #   #             Total                493          -           493
|  .   .   #   #   #         Missing                -
+----------------------                         -----
-.7285563      .9898975                           493
(More than 99 unique values)
```

Regressing γ^+ on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     493
-------------+------------------------------           F(  5,   487) =    0.96
       Model |  .386615252     5   .07732305           Prob > F      =  0.4419
    Residual |  39.2246376   487  .080543404           R-squared     =  0.0098
-------------+------------------------------           Adj R-squared = -0.0004
       Total |  39.6112529   492  .080510677           Root MSE      =   .2838

------------------------------------------------------------------------------
  gamma_gain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2   |  -.0223199   .0399601    -0.56   0.577    -.1008354    .0561955
PullMinus1   |  -.0471886   .0424804    -1.11   0.267     -.130656    .0362789
Pull1        |   .0290974   .0416804     0.70   0.485    -.0527982     .110993
Pull2        |   .0186381   .0403513     0.46   0.644    -.0606461    .0979223
     dum_wEV |  -.0170039   .0256921    -0.66   0.508    -.0674849    .0334772
       _cons |   .3764764   .0329598    11.42   0.000     .3117154    .4412374
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1  = 0
 ( 3)  Pull1  = 0
 ( 4)  Pull2 = 0

       F(  4,   487) =    1.11
            Prob > F =    0.3490
```

Regressing γ^+ on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     493
-------------+------------------------------           F(  2,   490) =    1.64
       Model |  .264173516     2  .132086758           Prob > F      =  0.1941
    Residual |  39.3470794   490  .080300162           R-squared     =  0.0067
-------------+------------------------------           Adj R-squared =  0.0026
       Total |  39.6112529   492  .080510677           Root MSE      =  .28337

------------------------------------------------------------------------------
  gamma_gain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0149656     .00872     1.72   0.087    -.0021675    .0320988
      dum_EV |  -.0179647   .0255904    -0.70   0.483    -.0682452    .0323157
       _cons |   .3732692   .0182798    20.42   0.000     .3373528    .4091856
------------------------------------------------------------------------------
```

Identity Probability Function (w(p)=p): Analyses for γ^-

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
  gamma_loss |       489    .2042293    .2769823  -.8432078   .9866828

gamma_loss:                                                Number of Observations
--------                                            ------------------------------
                                                     Total   Integers   Nonintegers
|             #             Negative                  100          -          100
|         #   #             Zero                        -          -            -
|         #   #             Positive                  389          -          389
|         #   #                                     -----      -----        -----
|         #   #             Total                     489          -          489
|  .   #  #   #   .         Missing                     -
+----------------------                             -----
-.8432078      .9866828                               489
(More than 99 unique values)
```

Regressing γ^- on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     489
-------------+------------------------------           F(  5,   483) =    6.94
       Model |  2.50893895     5   .50178779           Prob > F      =  0.0000
    Residual |  34.9300269   483  .072318896           R-squared     =  0.0670
-------------+------------------------------           Adj R-squared =  0.0574
       Total |  37.4389659   488  .076719192           Root MSE      =  .26892

------------------------------------------------------------------------------
  gamma_loss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2   |  -.1739069   .0380855    -4.57   0.000    -.2487405   -.0990733
PullMinus1   |  -.0707907   .0397999    -1.78   0.076     -.148993    .0074116
Pull1        |  -.0133678   .0395978    -0.34   0.736     -.091173    .0644374
Pull2        |   .0129724   .0379416     0.34   0.733    -.0615785    .0875234
     dum_wEV |  -.0319599   .0244429    -1.31   0.192    -.0799875    .0160677
       _cons |   .2708673   .0307444     8.81   0.000     .2104579    .3312766
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1  = 0
 ( 3)  Pull1  = 0
 ( 4)  Pull2 = 0

       F(  4,   483) =    8.48
            Prob > F =    0.0000
```

Regressing γ^- on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     489
-------------+------------------------------           F(  2,   486) =   13.83
       Model |  2.01639564     2  1.00819782           Prob > F      =  0.0000
    Residual |  35.4225702   486  .072885947           R-squared     =  0.0539
-------------+------------------------------           Adj R-squared =  0.0500
       Total |  37.4389659   488  .076719192           Root MSE      =  .26997

------------------------------------------------------------------------------
  gamma_loss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0435236   .0083923     5.19   0.000     .0270339    .0600132
      dum_EV |  -.0303114   .0244779    -1.24   0.216     -.078407    .0177843
       _cons |   .2191219    .017337    12.64   0.000     .1850571    .2531867
------------------------------------------------------------------------------
```

One-parameter function used by T&K:
Analyses for γ^+

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
  gamma_gain |       487    .2726035    .2484334  -.7066774   .9352897
```

```
gamma_gain:                                         Number of Observations
--------                                      ------------------------------
                                              Total   Integers   Nonintegers
|             #             Negative             57          -            57
|             #             Zero                  -          -             -
|         #   #             Positive            430          -           430
|         #   #                                 -----      -----       -----
|         #   #             Total               487          -           487
|  .   .  #   #   .         Missing               -
+----------------------                         -----
-.7066774      .9352897                         487
(More than 99 unique values)
```

Regressing γ^+ on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     487
-------------+------------------------------           F(  5,   481) =    4.51
       Model |  1.34249071     5  .268498141           Prob > F      =  0.0005
    Residual |  28.6530258   481   .0595697            R-squared     =  0.0448
-------------+------------------------------           Adj R-squared =  0.0348
       Total |  29.9955165   486   .06171917           Root MSE      =  .24407

------------------------------------------------------------------------------
  gamma_gain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2   |  -.0505554   .0344287    -1.47   0.143    -.1182046    .0170937
PullMinus1   |  -.0737976   .0367534    -2.01   0.045    -.1460147   -.0015805
Pull1        |   .0460543   .0359347     1.28   0.201     -.024554    .1166626
Pull2        |   .0568465   .0348546     1.63   0.104    -.0116397    .1253327
     dum_wEV |    .017834   .0222274     0.80   0.423    -.0258407    .0615088
       _cons |   .2669045   .0283784     9.41   0.000     .2111435    .3226654
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1  = 0
 ( 3)  Pull1  = 0
 ( 4)  Pull2 = 0

       F(  4,   481) =    5.36
            Prob > F =    0.0003
```

Regressing γ^+ on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     487
-------------+------------------------------           F(  2,   484) =    9.69
       Model |  1.15477029     2  .577385143           Prob > F      =  0.0001
    Residual |  28.8407463   484  .059588319           R-squared     =  0.0385
-------------+------------------------------           Adj R-squared =  0.0345
       Total |  29.9955165   486   .06171917           Root MSE      =  .24411

------------------------------------------------------------------------------
  gamma_gain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0323339   .0075652     4.27   0.000     .0174692    .0471987
      dum_EV |   .0169365   .0221816     0.76   0.446    -.0266476    .0605206
       _cons |   .2643076   .0158799    16.64   0.000     .2331056    .2955096
------------------------------------------------------------------------------
```

One-parameter function used by T&K:
Analyses for γ^-

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
  gamma_loss |       477    .1180496    .2853667  -1.018888    .986672

gamma_loss:                                          Number of Observations
--------                                        ------------------------------
                                                 Total   Integers   Nonintegers
|              #            Negative               136          -           136
|          #   #            Zero                     -          -             -
|          #   #            Positive               341          -           341
|          #   #                                 -----      -----         -----
|          #   #            Total                  477          -           477
|  .   #   #   #   .        Missing                  -
+----------------------                          -----
-1.018888       .986672                            477
(More than 99 unique values)
```

Regressing γ^- on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     477
-------------+------------------------------           F(  5,   471) =    8.28
       Model |  3.13179476     5  .626358951           Prob > F      =  0.0000
    Residual |   35.630864   471  .075649393           R-squared     =  0.0808
-------------+------------------------------           Adj R-squared =  0.0710
       Total |  38.7626588   476  .081434157           Root MSE      =  .27504

------------------------------------------------------------------------------
  gamma_loss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2   |   -.167102   .0393276    -4.25   0.000    -.2443813   -.0898226
PullMinus1   |  -.0397786   .0412873    -0.96   0.336    -.1209088    .0413515
Pull1        |   .0487408   .0409575     1.19   0.235    -.0317412    .1292228
Pull2        |   .0425907   .0390072     1.09   0.275    -.0340589    .1192403
     dum_wEV |  -.0119161   .0253293    -0.47   0.638    -.0616885    .0378564
       _cons |   .1490208   .0316051     4.72   0.000     .0869164    .2111253
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1  = 0
 ( 3)  Pull1  = 0
 ( 4)  Pull2 = 0

       F(  4,   471) =   10.35
            Prob > F =    0.0000
```

Regressing γ^- on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     477
-------------+------------------------------           F(  2,   474) =   17.20
       Model |  2.62317384     2  1.31158692           Prob > F      =  0.0000
    Residual |  36.1394849   474  .076243639           R-squared     =  0.0677
-------------+------------------------------           Adj R-squared =  0.0637
       Total |  38.7626588   476  .081434157           Root MSE      =  .27612

------------------------------------------------------------------------------
  gamma_loss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0509247   .0086825     5.87   0.000     .0338638    .0679855
      dum_EV |  -.0125041    .025354    -0.49   0.622    -.0623242     .037316
       _cons |   .1233802   .0179526     6.87   0.000     .0881037    .1586566
------------------------------------------------------------------------------
```

Two-parameter function suggested by Goldstein and Einhorn (1987) and Lattimore, Baker, and Witte (1992):
Analyses for γ^+

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
  gamma_gain |       467    .3701047    .2608631  -.6311136   .9999057
```

```
gamma_gain:                                         Number of Observations
--------                                     ------------------------------
                                             Total   Integers   Nonintegers
|              #             Negative           41          -            41
|          #   #             Zero                -          -             -
|          #   #             Positive          426          -           426
|          #   #                             -----      -----         -----
|          #   #             Total             467          -           467
|   .   #  #   #   #         Missing             -
+----------------------                      -----
-.6311136      .9999057                        467
(More than 99 unique values)
```

Regressing γ^+ on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     467
-------------+------------------------------           F(  5,   461) =    2.98
       Model |  .993488669     5  .198697734           Prob > F      =  0.0116
    Residual |  30.7175968   461  .066632531           R-squared     =  0.0313
-------------+------------------------------           Adj R-squared =  0.0208
       Total |  31.7110855   466   .06804954           Root MSE      =  .25813

------------------------------------------------------------------------------
  gamma_gain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2   |  -.0143445   .0374513    -0.38   0.702     -.087941     .059252
PullMinus1   |  -.0462537   .0400086    -1.16   0.248    -.1248756    .0323682
Pull1        |   .0605392   .0390046     1.55   0.121    -.0161097    .1371882
Pull2        |   .0733702   .0377909     1.94   0.053    -.0008935     .147634
     dum_wEV |   .0166382   .0240377     0.69   0.489    -.0305988    .0638753
       _cons |   .3452017   .0311466    11.08   0.000     .2839949    .4064086
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1  = 0
 ( 3)  Pull1  = 0
 ( 4)  Pull2 = 0

       F(  4,   461) =    3.56
            Prob > F =    0.0071
```

Regressing γ^+ on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     467
-------------+------------------------------           F(  2,   464) =    5.87
       Model |  .782361852     2  .391180926           Prob > F      =  0.0030
    Residual |  30.9287237   464  .066656732           R-squared     =  0.0247
-------------+------------------------------           Adj R-squared =  0.0205
       Total |  31.7110855   466   .06804954           Root MSE      =  .25818

------------------------------------------------------------------------------
  gamma_gain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |    .027071    .008139     3.33   0.001      .011077    .0430649
      dum_EV |   .0141684   .0239599     0.59   0.555     -.032915    .0612517
       _cons |   .3629973   .0171594    21.15   0.000     .3292775     .396717
------------------------------------------------------------------------------
```

Two-parameter function suggested by Goldstein and Einhorn (1987) and Lattimore, Baker, and Witte (1992):

Analyses for γ^-

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
  gamma_loss |       464    .1816388    .2921639  -.9297704   .9999807
```

```
gamma_loss:                                         Number of Observations
--------                                     ------------------------------
                                             Total   Integers   Nonintegers
|          #   #             Negative          104          -           104
|          #   #             Zero                -          -             -
|          #   #             Positive          360          -           360
|          #   #                             -----      -----         -----
|          #   #             Total             464          -           464
|  .   #   #   #   .         Missing             -
+----------------------                      -----
-.9297704      .9999807                        464
(More than 99 unique values)
```

Regressing γ^- on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     464
-------------+------------------------------           F(  5,   458) =    6.57
       Model |  2.64498932     5  .528997864           Prob > F      =  0.0000
    Residual |  36.8765629   458  .080516513           R-squared     =  0.0669
-------------+------------------------------           Adj R-squared =  0.0567
       Total |  39.5215522   463  .085359724           Root MSE      =  .28375

------------------------------------------------------------------------------
  gamma_loss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2   |  -.1386059   .0410945    -3.37   0.001     -.219363   -.0578488
PullMinus1   |  -.0422493   .0437038    -0.97   0.334    -.1281341    .0436356
Pull1        |   .0238077   .0429602     0.55   0.580    -.0606158    .1082311
Pull2        |   .0631686   .0411963     1.53   0.126    -.0177887    .1441259
     dum_wEV |  -.0544877   .0264923    -2.06   0.040    -.1065491   -.0024262
       _cons |   .2300767   .0336536     6.84   0.000     .1639422    .2962113
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1  = 0
 ( 3)  Pull1  = 0
 ( 4)  Pull2 = 0

       F(  4,   458) =    7.51
            Prob > F =    0.0000
```

Regressing γ^- on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     464
-------------+------------------------------           F(  2,   461) =   15.46
       Model |  2.48435424     2  1.24217712           Prob > F      =  0.0000
    Residual |   37.037198   461  .080340993           R-squared     =  0.0629
-------------+------------------------------           Adj R-squared =  0.0588
       Total |  39.5215522   463  .085359724           Root MSE      =  .28344

------------------------------------------------------------------------------
  gamma_loss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0476252   .0089821     5.30   0.000     .0299743    .0652761
      dum_EV |  -.0531612   .0263879    -2.01   0.045    -.1050165   -.0013058
       _cons |   .2089306   .0189572    11.02   0.000     .1716775    .2461838
------------------------------------------------------------------------------
```

ONLINE APPENDIX III.B
Robustness of Main Results for γ^+, γ^-, and λ to Rule for Dropping Outliers

To test the robustness of our results to the rule for dropping outliers, we also look at the effects of changing our cutoff for dropping outliers from four standard deviations from the mean to three, five, and six standard deviations from the mean. Results of these analyses are reported below.

Changing the Cutoff to Three Standard Deviations From the Mean: Analyses for γ^+

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
  gamma_gain |       454    .3380039    .1694515   -.131243    .777787
```

```
gamma_gain:                                          Number of Observations
--------                                    ------------------------------
                                            Total   Integers   Nonintegers
|          #                 Negative          15          -            15
|          #                 Zero               -          -             -
|          #                 Positive         439          -           439
|          #   #                            -----      -----         -----
|      #   #   #             Total            454          -           454
|   .  #   #   #   .         Missing            -
+----------------------                     -----
-.131243        .777787                       454
(More than 99 unique values)
```

Regressing γ^+ on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     454
-------------+------------------------------           F(  5,   448) =    9.11
       Model |  1.20016094     5  .240032187           Prob > F      =  0.0000
    Residual |  11.8071943   448  .026355344           R-squared     =  0.0923
-------------+------------------------------           Adj R-squared =  0.0821
       Total |  13.0073552   453  .028713808           Root MSE      =  .16234

------------------------------------------------------------------------------
gamma_gain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2 |  -.0549723   .0242741    -2.26   0.024    -.1026775   -.0072671
PullMinus1 |  -.0326196    .025405    -1.28   0.200    -.0825474    .0173082
Pull1      |   .0643795   .0247236     2.60   0.010     .0157909    .1129681
Pull2      |    .064664    .023819     2.71   0.007     .0178532    .1114748
dum_EV     |   .0168691   .0153503     1.10   0.272    -.0132984    .0470365
_cons      |   .3195175   .0196856    16.23   0.000     .2808299     .358205
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1 = 0
 ( 3)  Pull1 = 0
 ( 4)  Pull2 = 0

       F(  4,   448) =   10.72
            Prob > F =    0.0000
```

Regressing γ^+ on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     454
-------------+------------------------------           F(  2,   451) =   21.49
       Model |  1.13182932     2  .565914659           Prob > F      =  0.0000
    Residual |  11.8755259   451  .026331543           R-squared     =  0.0870
-------------+------------------------------           Adj R-squared =  0.0830
       Total |  13.0073552   453  .028713808           Root MSE      =  .16227

------------------------------------------------------------------------------
gamma_gain   |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       Pull  |   .0332073   .0052301     6.35   0.000     .0229289    .0434858
      dum_EV |   .0154289   .0153055     1.01   0.314    -.0146501    .0455079
       _cons |   .3285052   .0108532    30.27   0.000     .3071761    .3498343
------------------------------------------------------------------------------
```

Changing the Cutoff to Three Standard Deviations From the Mean: Analyses for γ^{-}

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
gamma_loss   |       457    .3152673    .1919398  -.2231644   .7500039
```

```
gamma_loss:                                          Number of Observations
--------                                          ------------------------------
                                                   Total   Integers   Nonintegers
|              #             Negative                35         -            35
|          #   #             Zero                     -         -             -
|          #   #             Positive               422         -           422
|          #   #                                  -----     -----         -----
|      #   #   #             Total                  457         -           457
|  .   #   #   #   #         Missing                  -
+----------------------                           -----
-.2231644      .7500039                             457
(More than 99 unique values)
```

Regressing γ^- on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     457
-------------+------------------------------           F(  5,   451) =    9.17
       Model |  1.55091047     5  .310182093           Prob > F      =  0.0000
    Residual |  15.2485384   451  .033810506           R-squared     =  0.0923
-------------+------------------------------           Adj R-squared =  0.0823
       Total |  16.7994489   456  .036840897           Root MSE      =  .18388

------------------------------------------------------------------------------
gamma_loss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2 |  -.0754656   .0273066    -2.76   0.006    -.1291295   -.0218017
PullMinus1 |  -.0255904   .0287625    -0.89   0.374    -.0821156    .0309348
Pull1      |   .0640351   .0280027     2.29   0.023     .0090031     .119067
Pull2      |   .0741114   .0269783     2.75   0.006     .0210927    .1271301
dum_EV     |  -.0274873   .0173277    -1.59   0.113    -.0615403    .0065657
_cons      |   .3208781   .0222824    14.40   0.000     .2770879    .3646682
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1 = 0
 ( 3)  Pull1 = 0
 ( 4)  Pull2 = 0

       F(  4,   451) =   11.20
            Prob > F =    0.0000
```

Regressing γ^- on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     457
-------------+------------------------------           F(  2,   454) =   22.26
       Model |  1.50047251     2  .750236257           Prob > F      =  0.0000
    Residual |  15.2989764   454  .033698186           R-squared     =  0.0893
-------------+------------------------------           Adj R-squared =  0.0853
       Total |  16.7994489   456  .036840897           Root MSE      =  .18357

------------------------------------------------------------------------------
gamma_loss   |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0387564   .0058784     6.59   0.000     .0272042    .0503087
      dum_EV |  -.0286548   .0172568    -1.66   0.098    -.0625678    .0052583
       _cons |   .3283724   .0122541    26.80   0.000     .3042906    .3524542
------------------------------------------------------------------------------
```

Changing the Cutoff to Three Standard Deviations From the Mean: Analyses for λ

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
      lambda |       431    1.181653    .7905708   .0118026   3.740709

lambda:                                             Number of Observations
---------                                       ------------------------------
                                                Total   Integers   Nonintegers
|       #                    Negative               -          -             -
|   #   #                    Zero                   -          -             -
|   #   #                    Positive             431          -           431
|   #   #                                       -----      -----         -----
|   #   #   #                Total                431          -           431
|   #   #   #   #   .        Missing                -
+----------------------                         -----
.0118026       3.740709                           431
(More than 99 unique values)
```

Regressing λ on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     431
-------------+------------------------------           F(  5,   425) =    1.94
       Model |  6.00200767     5  1.20040153           Prob > F      =  0.0863
    Residual |  262.748918   425  .618232749           R-squared     =  0.0223
-------------+------------------------------           Adj R-squared =  0.0108
       Total |  268.750926   430  .625002153           Root MSE      =  .78628

------------------------------------------------------------------------------
Lambda      |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2 |   .0108982   .1199637     0.09   0.928    -.2248977    .2466942
PullMinus1 |   .1187597   .1249991     0.95   0.343    -.1269336    .3644531
Pull1      |  -.1665329   .1225537    -1.36   0.175    -.4074197    .0743538
Pull2      |  -.1925727   .1189573    -1.62   0.106    -.4263906    .0412453
dum_EV     |  -.0238138   .0764978    -0.31   0.756    -.1741749    .1265472
_cons      |   1.244978   .0975695    12.76   0.000     1.053199    1.436757
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1 = 0
 ( 3)  Pull1 = 0
 ( 4)  Pull2 = 0

       F(  4,   425) =    2.34
            Prob > F =    0.0540
```

Regressing λ on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     431
-------------+------------------------------           F(  2,   428) =    3.47
       Model |  4.28308531     2  2.14154265           Prob > F      =  0.0321
    Residual |  264.467841   428  .617915515           R-squared     =  0.0159
-------------+------------------------------           Adj R-squared =  0.0113
       Total |  268.750926   430  .625002153           Root MSE      =  .78608

------------------------------------------------------------------------------
      lambda |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |  -.0672832   .0261857    -2.57   0.011    -.1187519   -.0158146
      dum_EV |  -.0204504   .0762908    -0.27   0.789    -.1704015    .1295008
       _cons |   1.193748   .0545216    21.89   0.000     1.086584    1.300911
------------------------------------------------------------------------------
```

Changing the Cutoff to Five Standard Deviations From the Mean: Analyses for γ^{+}

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
gamma_gain   |       462    .3290559    .1891919  -.5483738   .8790295
```

```
gamma_gain:                                          Number of Observations
--------                                        ------------------------------
                                                Total   Integers   Nonintegers
|             #             Negative               22          -            22
|             #             Zero                    -          -             -
|         #   #             Positive              440          -           440
|         #   #                                 -----      -----         -----
|         #   #             Total                 462          -           462
|  .   .  #   #   .         Missing                 -
+----------------------                         -----
-.5483738      .8790295                           462
(More than 99 unique values)
```

Regressing γ^+ on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     462
-------------+------------------------------           F(  5,   456) =   10.90
       Model |   1.7621494     5   .35242988           Prob > F      =  0.0000
    Residual |  14.7386926   456  .032321694           R-squared     =  0.1068
-------------+------------------------------           Adj R-squared =  0.0970
       Total |   16.500842   461  .035793583           Root MSE      =  .17978

------------------------------------------------------------------------------
gamma_gain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2 |  -.0911752   .0264703    -3.44   0.001     -.143194   -.0391563
PullMinus1 |  -.0567164   .0278692    -2.04   0.042    -.1114845   -.0019484
Pull1      |     .05711   .0272911     2.09   0.037     .0034782    .1107419
Pull2      |   .0584122   .0262937     2.22   0.027     .0067403    .1100841
dum_EV     |   .0070262   .0168385     0.42   0.677    -.0260645     .040117
_cons      |   .3315425   .0216089    15.34   0.000     .2890771    .3740079
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1 = 0
 ( 3)  Pull1 = 0
 ( 4)  Pull2 = 0

       F(  4,   456) =   13.37
            Prob > F =    0.0000
```

Regressing γ^+ on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     462
-------------+------------------------------           F(  2,   459) =   25.93
       Model |  1.67527632     2   .83763816           Prob > F      =  0.0000
    Residual |  14.8255657   459  .032299707           R-squared     =  0.1015
-------------+------------------------------           Adj R-squared =  0.0976
       Total |   16.500842   461  .035793583           Root MSE      =  .17972

------------------------------------------------------------------------------
gamma_gain   |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0407932    .005723     7.13   0.000     .0295468    .0520396
      dum_EV |   .0061023   .0167966     0.36   0.717    -.0269053      .03911
       _cons |   .3249938   .0119202    27.26   0.000     .3015689    .3484187
------------------------------------------------------------------------------
```

Changing the Cutoff to Five Standard Deviations From the Mean: Analyses for γ^-

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
gamma_loss   |       463     .311811    .2070169   -.700062   .9957242

gamma_loss:                                          Number of Observations
--------                                      ------------------------------
                                              Total   Integers   Nonintegers
|              #            Negative             39          -            39
|              #            Zero                  -          -             -
|          #   #            Positive            424          -           424
|          #   #                              -----      -----         -----
|          #   #            Total               463          -           463
|  .   .   #   #   .        Missing               -
+----------------------                       -----
-.700062       .9957242                         463
(More than 99 unique values)
```

Regressing γ^- on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     463
-------------+------------------------------           F(  5,   457) =    8.63
       Model |  1.70759424     5  .341518848           Prob > F      =  0.0000
    Residual |  18.0918681   457  .039588333           R-squared     =  0.0862
-------------+------------------------------           Adj R-squared =  0.0762
       Total |  19.7994624   462  .042855979           Root MSE      =  .19897

------------------------------------------------------------------------------
gamma_loss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2 |  -.0941467    .029295    -3.21   0.001    -.1517163    -.036577
PullMinus1 |  -.0323022   .0308433    -1.05   0.296    -.0929145    .0283101
Pull1      |   .0562269   .0302034     1.86   0.063    -.0031279    .1155818
Pull2      |   .0574569    .029039     1.98   0.048     .0003903    .1145235
dum_EV     |  -.0397942   .0186217    -2.14   0.033    -.0763889   -.0031995
_cons      |   .3346322   .0239116    13.99   0.000     .2876418    .3816226
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1 = 0
 ( 3)  Pull1 = 0
 ( 4)  Pull2 = 0

       F(  4,   457) =   10.13
            Prob > F =    0.0000
```

Regressing γ^- on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     463
-------------+------------------------------           F(  2,   460) =   20.40
       Model |  1.61315084     2  .806575418           Prob > F      =  0.0000
    Residual |  18.1863115   460   .03953546           R-squared     =  0.0815
-------------+------------------------------           Adj R-squared =  0.0775
       Total |  19.7994624   462  .042855979           Root MSE      =  .19884

------------------------------------------------------------------------------
gamma_loss   |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0390494   .0063208     6.18   0.000     .0266282    .0514706
      dum_EV |  -.0409418    .018568    -2.20   0.028    -.0774303   -.0044532
       _cons |    .331495   .0131879    25.14   0.000      .305579     .357411
------------------------------------------------------------------------------
```

Changing the Cutoff to Five Standard Deviations From the Mean: Analyses for λ

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
      lambda |       446    1.308201    1.041592   .0118026   6.419184
```

```
lambda:                                          Number of Observations
---------                                    ------------------------------
                                             Total   Integers   Nonintegers
|  #                            Negative         -          -             -
|  #                            Zero             -          -             -
|  #                            Positive       446          -           446
|  #                                         -----      -----         -----
|  #   #                        Total          446          -           446
|  #   #   .   .   .            Missing          -
+----------------------                      -----
.0118026       6.419184                        446
(More than 99 unique values)
```

Regressing λ on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     446
-------------+------------------------------           F(  5,   440) =    0.88
       Model |  4.79080373     5  .958160746           Prob > F      =  0.4930
    Residual |  477.996111   440   1.0863548           R-squared     =  0.0099
-------------+------------------------------           Adj R-squared = -0.0013
       Total |  482.786915   445  1.08491441           Root MSE      =  1.0423

------------------------------------------------------------------------------
lambda     |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2 |   .1801269   .1559928     1.15   0.249    -.1264567    .4867104
PullMinus1 |   .0626959   .1651479     0.38   0.704    -.2618808    .3872726
Pull1      |  -.1115648   .1606104    -0.69   0.488    -.4272236    .2040939
Pull2      |  -.0419179   .1553563    -0.27   0.787    -.3472506    .2634148
dum_EV     |  -.0302106   .0995412    -0.30   0.762    -.2258458    .1654246
_cons      |   1.303994    .127931    10.19   0.000     1.052562    1.555426
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1 = 0
 ( 3)  Pull1 = 0
 ( 4)  Pull2 = 0

       F(  4,   440) =    1.05
            Prob > F =    0.3784
```

Regressing λ on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     446
-------------+------------------------------           F(  2,   443) =    1.76
       Model |  3.79731824     2  1.89865912           Prob > F      =  0.1739
    Residual |  478.989596   443  1.08124062           R-squared     =  0.0079
-------------+------------------------------           Adj R-squared =  0.0034
       Total |  482.786915   445  1.08491441           Root MSE      =  1.0398

------------------------------------------------------------------------------
      lambda |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |  -.0614366   .0337126    -1.82   0.069     -.127693    .0048198
      dum_EV |  -.0252266   .0990077    -0.25   0.799    -.2198097    .1693564
       _cons |   1.322726   .0708767    18.66   0.000     1.183429    1.462022
------------------------------------------------------------------------------
```

Changing the Cutoff to Six Standard Deviations From the Mean: Analyses for γ^+

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
gamma_gain   |       463     .326849    .1948618   -.692746   .8790295

gamma_gain:                                           Number of Observations
--------                                        ------------------------------
                                                Total   Integers   Nonintegers
|             #             Negative               23          -            23
|             #             Zero                    -          -             -
|             #             Positive              440          -           440
|             #                                 -----      -----         -----
|         #   #             Total                 463          -           463
|  .   .  #   #   .         Missing                 -
+----------------------                         -----
-.692746       .8790295                           463
(More than 99 unique values)
```

Regressing γ^+ on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     463
-------------+------------------------------           F(  5,   457) =    9.36
       Model |  1.62952273     5  .325904546           Prob > F      =  0.0000
    Residual |  15.9131434   457  .034820883           R-squared     =  0.0929
-------------+------------------------------           Adj R-squared =  0.0830
       Total |  17.5426661   462  .037971139           Root MSE      =   .1866

------------------------------------------------------------------------------
gamma_gain |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2 |   -.091612   .0274745    -3.33   0.001    -.1456041     -.03762
PullMinus1 |  -.0570664   .0289266    -1.97   0.049     -.113912   -.0002208
Pull1      |   .0568372   .0283265     2.01   0.045     .0011709    .1125035
Pull2      |   .0481806   .0272344     1.77   0.078    -.0053397    .1017008
dum_EV     |   .0031172   .0174644     0.18   0.858    -.0312034    .0374378
_cons      |   .3337039   .0224257    14.88   0.000     .2896337    .3777742
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1 = 0
 ( 3)  Pull1 = 0
 ( 4)  Pull2 = 0

       F(  4,   457) =   11.56
            Prob > F =    0.0000
```

Regressing γ^+ on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     463
-------------+------------------------------           F(  2,   460) =   21.58
       Model |  1.50448168     2   .75224084           Prob > F      =  0.0000
    Residual |  16.0381844   460  .034865618           R-squared     =  0.0858
-------------+------------------------------           Adj R-squared =  0.0818
       Total |  17.5426661   462  .037971139           Root MSE      =  .18672

------------------------------------------------------------------------------
gamma_gain   |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0387444   .0059358     6.53   0.000     .0270798     .050409
      dum_EV |    .001972   .0174369     0.11   0.910    -.0322938    .0362379
       _cons |   .3247602   .0123846    26.22   0.000     .3004228    .3490975
------------------------------------------------------------------------------
```

Changing the Cutoff to Six Standard Deviations From the Mean: Analyses for γ^-

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
gamma_loss   |       463     .311811    .2070169   -.700062   .9957242
```

```
gamma_loss:                                         Number of Observations
--------                                   ------------------------------
                                           Total   Integers   Nonintegers
|              #             Negative         39          -            39
|              #             Zero              -          -             -
|          #   #             Positive        424          -           424
|          #   #                           -----      -----         -----
|          #   #             Total           463          -           463
|  .   .   #   #   .         Missing           -
+----------------------                    -----
-.700062       .9957242                      463
(More than 99 unique values)
```

Regressing γ^- on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     463
-------------+------------------------------           F(  5,   457) =    8.63
       Model |  1.70759424     5  .341518848           Prob > F      =  0.0000
    Residual |  18.0918681   457  .039588333           R-squared     =  0.0862
-------------+------------------------------           Adj R-squared =  0.0762
       Total |  19.7994624   462  .042855979           Root MSE      =  .19897

------------------------------------------------------------------------------
gamma_loss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2 |  -.0941467    .029295    -3.21   0.001    -.1517163    -.036577
PullMinus1 |  -.0323022   .0308433    -1.05   0.296    -.0929145    .0283101
Pull1      |   .0562269   .0302034     1.86   0.063    -.0031279    .1155818
Pull2      |   .0574569    .029039     1.98   0.048     .0003903    .1145235
dum_EV     |  -.0397942   .0186217    -2.14   0.033    -.0763889   -.0031995
_cons      |   .3346322   .0239116    13.99   0.000     .2876418    .3816226
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1 = 0
 ( 3)  Pull1 = 0
 ( 4)  Pull2 = 0

       F(  4,   457) =   10.13
            Prob > F =    0.0000
```

Regressing γ^- on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     463
-------------+------------------------------           F(  2,   460) =   20.40
       Model |  1.61315084     2  .806575418           Prob > F      =  0.0000
    Residual |  18.1863115   460   .03953546           R-squared     =  0.0815
-------------+------------------------------           Adj R-squared =  0.0775
       Total |  19.7994624   462  .042855979           Root MSE      =  .19884

------------------------------------------------------------------------------
gamma_loss   |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |   .0390494   .0063208     6.18   0.000     .0266282    .0514706
      dum_EV |  -.0409418    .018568    -2.20   0.028    -.0774303   -.0044532
       _cons |    .331495   .0131879    25.14   0.000      .305579     .357411
------------------------------------------------------------------------------
```

Changing the Cutoff to Six Standard Deviations From the Mean: Analyses for λ

Looking at the data after dropping the outliers:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
      lambda |       447    1.320869    1.074341   .0118026   6.970557
```

```
lambda:                                        Number of Observations
---------                                  ------------------------------
                                            Total   Integers   Nonintegers
|  #                          Negative          -          -             -
|  #                          Zero              -          -             -
|  #                          Positive        447          -           447
|  #                                        -----      -----         -----
|  #   #                      Total           447          -           447
|  #   #   .   .   .          Missing           -
+----------------------                     -----
.0118026       6.970557                       447
(More than 99 unique values)
```

Regressing λ on dummies for each Pull (except Pull 0, taken as the default) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     447
-------------+------------------------------           F(  5,   441) =    1.22
       Model |  7.03686794     5  1.40737359           Prob > F      =  0.2975
    Residual |  507.740588   441   1.1513392           R-squared     =  0.0137
-------------+------------------------------           Adj R-squared =  0.0025
       Total |  514.777456   446  1.15420954           Root MSE      =   1.073

------------------------------------------------------------------------------
lambda     |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PullMinus2 |   .2324969   .1602598     1.45   0.148    -.0824709    .5474647
PullMinus1 |   .0604609   .1700151     0.36   0.722    -.2736795    .3946013
Pull1      |  -.1133229    .165344    -0.69   0.493     -.438283    .2116372
Pull2      |   -.040816   .1599353    -0.26   0.799    -.3551461    .2735141
dum_EV     |   -.052687   .1023797    -0.51   0.607    -.2538997    .1485257
_cons      |   1.316603   .1316784    10.00   0.000     1.057807    1.575398
------------------------------------------------------------------------------
```

F-test for the joint significance of the four Pull dummies:

```
 ( 1)  PullMinus2 = 0
 ( 2)  PullMinus1 = 0
 ( 3)  Pull1 = 0
 ( 4)  Pull2 = 0

       F(  4,   441) =    1.41
            Prob > F =    0.2288
```

Regressing λ on a linear variable equal to Pull (-2, -1, 0, 1, 2) and a dummy for the expected value treatment (equal to 1 if the expected value was displayed):

```
      Source |       SS       df       MS              Number of obs =     447
-------------+------------------------------           F(  2,   444) =    2.40
       Model |  5.51472675     2  2.75736337           Prob > F      =  0.0915
    Residual |   509.26273   444  1.14698813           R-squared     =  0.0107
-------------+------------------------------           Adj R-squared =  0.0063
       Total |  514.777456   446  1.15420954           Root MSE      =   1.071

------------------------------------------------------------------------------
      lambda |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Pull |  -.0722358   .0346587    -2.08   0.038    -.1403513   -.0041202
      dum_EV |  -.0474598   .1018816    -0.47   0.642    -.2476898    .1527702
       _cons |   1.346743   .0728499    18.49   0.000      1.20357    1.489917
------------------------------------------------------------------------------
```