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ABSTRACT

The compromise effect arises when options near the "middle" of a choice set are more appealing. The compromise effect poses conceptual and practical problems for economic research: by influencing choices, it distorts revealed preferences, biasing researchers' inferences about deep (i.e., domain general) preferences. We propose and estimate an econometric model that disentangles and identifies both deep preferences and the context-dependent compromise effect. We demonstrate our method using data from an experiment with 550 participants who made choices over lotteries from multiple price lists. Following prior work, we manipulate the compromise effect by varying the middle options of each multiple price list and then estimate risk preferences without modelling the compromise effect. These naïve parameter estimates are not robust: they change as the compromise effect is manipulated. To eliminate this bias, we incorporate the compromise effect directly into our econometric model. We show that this method generates robust estimates of risk preference parameters that are no longer sensitive to compromise-effect manipulations. This method can be applied to other settings that exhibit the compromise effect.

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1 Introduction

The *compromise effect* arises when options in a choice set can be ordered on common dimensions or attributes (such as price, quantity, size, or intensity), and decision makers tend to select the options in the "middle" of the choice set. For example, suppose a group of respondents were asked whether they wanted a free nature hike of either 1 mile or 4 miles. Now suppose that a different, otherwise identical group were asked whether they preferred a free nature hike of 1, 4, or 7 miles. A compromise effect could lead to a *greater* fraction of respondents choosing 4 miles in the second choice set (see Simonson 1989 for a closely related empirical result and Kamenica 2008 for a discussion of microfoundations).

The compromise effect poses conceptual and practical problems for economic research. By influencing choices, the compromise effect distorts revealed preferences, biasing researchers' inferences about deep (i.e., domain general) preferences.

In this paper, we propose and estimate an econometric model that disentangles and separately identifies *both* the deep preferences and the (situational) compromise effect that is influencing the expression of those deep preferences. To demonstrate our approach, we conduct a laboratory experiment with 550 participants in which we elicit risk preferences using a multiple price list (MPL). We study this context because, despite the limitations of the MPL procedure, it is among the most commonly used methods to elicit preferences in the economics literature (e.g., Tversky and Kahneman 1992, Holt and Laury 2002, Harrison, List, and Towe 2007, Andersen, Harrison, Lau, and Rutström 2008) and because the compromise effect has been carefully and robustly documented already in the context of inferring risk preferences using an MPL (Birnbaum 1992, Harrison, Lau, Rutström, and Sullivan 2005, Andersen, Harrison, Lau, and Rutström 2006, Harrison, Lau, and Rutström 2007). We use the term compromise effect as short-hand for a bias toward the middle option, which is what these papers document.

The screenshot below is drawn from our own experiment and is typical of MPL experiments. In this example, a participant is asked to make seven binary choices. Each of the seven choices is between a gamble and a sure-thing alternative. The gamble doesn't change across the seven rows, while the sure-thing 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 $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

A subject who displayed a strong compromise effect would act as if she were indifferent between the gamble and the sure-thing in the middle row, which is row (d). Such indifference would imply that she is risk seeking because the gamble has a lower expected value than the sure thing in row (d). In this example, a strong compromise effect would lead a participant who may otherwise be risk-averse to make risk-seeking choices.

Following prior work (Birnbaum 1992, Harrison, Lau, Rutström, and Sullivan 2005, Andersen, Harrison, Lau, and Rutström 2006, Harrison, Lau, and Rutström 2007, and Harrison, List, and Towe 2007), we experimentally vary the middle option using scale manipulations. Specifically, we hold the lowest and highest alternatives of the MPL fixed and manipulate the locations of the five intermediate outcomes within the scale. For example, compare the screenshot above to the screenshot that follows, which has new alternatives in rows (b) through (f), although rows (a) and (g) are the same. With respect to this second MPL, an agent who acts as if the middle option, row (d), is her indifference point would be judged to be risk averse.

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

In our experiment, each participant is exposed to one of five different scale treatment conditions.

To econometrically disentangle risk preferences from the compromise effect, we augment a discrete-choice model with additional parameters that represent a penalty for choosing a switch point further from the middle. Note that our approach of incorporating the compromise effect into the econometric model is different from including treatment-condition indicators as controls. Simply controlling for treatment condition would not identify domain-general preferences because the compromise effect can influence choices in *every* treatment condition (i.e., there is no benchmark, compromise-effect-free treatment condition).

The deep preferences we study in the current paper are prospect-theoretic preferences over risky lotteries (e.g., Tversky and Kahneman 1992, Wakker 2010, Bruhin, Fehr-Duda, and Epper 2010). Our ex-ante hypotheses focus on two parameters: curvature γ (which captures risk aversion over gains and risk seeking over losses) and loss aversion λ (which captures the degree to which people dislike losses more than they like gains).[1] Our analysis yields three main findings.

First, our estimates of the compromise-effect parameters replicate the findings from earlier work that participants have a bias toward choosing a switch point in the middle rows of the MPL (e.g., Harrison, Lau, Rutström, and Sullivan 2005; see other references above). Moreover, our quantitative estimates indicate that the bias is sizeable; we estimate that the attractiveness of the middle rows relative to the extreme rows represents 17%-23% of the prospects' monetary value.

Second, when we estimate the prospect-theory model without controls for the compromise effect, the scale manipulations have a very powerful effect on the (mis-) estimated preference parameters. In particular, the compromise effect is strong enough to cause us to estimate either risk seeking (as predicted by prospect theory) or risk aversion (the opposite of what is predicted by prospect theory) in the loss domain, depending on the scale manipulations. The compromise effect is also strong enough that, when manipulated, it can make behavior look as if there is essentially no loss aversion (see the results for the Pull 2 treatment below).

Third, when we estimate the prospect-theory parameters while including additional parameters to capture the compromise effect, our estimates of γ and λ are robust across the five scale treatment conditions. The robustness of these preference-parameter estimates implies that they are not biased

[1] We predicted that our scaling manipulations would not substantially change the estimated parameters of the probability weighting function, because the prospects all have "probability-flipped" variants: i.e., for each MPL featuring a prospect with probability p of monetary outcome x_H and probability $1-p$ of monetary outcome x_L, the experiment includes another MPL featuring a probability-flipped prospect with probability $1-p$ of outcome x_H and probability p of outcome x_L. Scaling manipulations will have (approximately) offsetting effects with respect to the probability weighting function for these two probability-flipped prospects.

by the compromise effect. (When estimating the model pooling all of our experimental data, our estimates are $\hat{\gamma} = 0.24$ and $\hat{\lambda} = 1.31$, which fall within the range of estimates in the existing literature, albeit with $\hat{\lambda}$ toward the lower end of the range.)

In addition to the scale manipulations described above, we also study the effect of telling experimental participants the expected value of the risky prospects. We hypothesized that this manipulation would anchor the participants on the expected value, thereby nudging their preferences toward risk neutrality. However, we find that expected value information does not affect measured risk aversion nor measured loss aversion. Our null effect echoes the findings of Lichtenstein, Slovic, and Zink (1969) and Montgomery and Adelbratt (1982). However, Harrison and Rutström (2008) do find that providing expected value information significantly decreases risk aversion. The difference may arise because the prospects in their experiment are relatively complex, each involving four possible outcomes (versus one or two in our experiment).

This paper contributes to the literature on the compromise effect by estimating a model that explicitly accounts for the compromise effect and enables us to separately estimate it from risk preferences. Our sample is substantially larger than those used in earlier work, which allows us to precisely estimate the effects of the scale manipulations. Moreover, 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. In addition, we provide estimates of the economic magnitude and importance of the compromise effect relative to the prospects' monetary value, and we examine the demographic correlates of the parameters in our econometric model. A limitation of our experiment is that only one out of its four parts (which involves 28 of the 62 sets of choices we analyze) is incentivized. Reassuringly, all of our results still hold when we restrict attention to the incentivized data.

The rest of the paper is organized as follows. In Section 2, we discuss our experimental design. In Section 3, we describe our econometric discrete-choice model, which incorporates the compromise effect. In Section 4, we list and discuss the five formal hypotheses that we test. In Section 5, we report the results of the estimation of our model, and we test the robustness of the estimates to the scale manipulations. Section 6 parallels Section 5 but examines the prospect-theory model without controls for the compromise effect. Section 7 estimates the economic magnitude and importance of the compromise effect in our data. Sections 8 briefly analyzes the demographic correlates of the main parameters of our econometric model (including γ, λ, and parameters that capture the compromise effect). Section 9 briefly discusses the results of our expected value manipulation. Section 10 concludes.

2 Experiment

2.1 Design

Throughout the experiment, we employ the Multiple Price List (MPL) elicitation method (Tversky and Kahneman 1992, Holt and Laury 2002). 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* (or *alternative prospect*). The alternatives vary within a screen, with one alternative for each of the seven binary choices. In some (but not all) cases, the alternatives are sure things. Screenshots of the experiment are shown in the Introduction as well as in the Appendix, and the original instructions of the experiment are shown in the Online Appendix.

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 alternatives—to closely follow Tversky and Kahneman's (1992; henceforth T&K) experiment in their paper that introduced Cumulative Prospect Theory (CPT). 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.[2] Our algorithm for generating the seven alternatives is explained in Section 2.2 and in the Online Appendix, where we also list the complete set of fixed prospects and alternatives.[3]

[2] More precisely, participants have to select only two circles: the one corresponding to the worst alternative outcome they prefer to the fixed prospect and the one corresponding to the fixed prospect in the following row. The other circles are auto-filled. This procedure is a version of the "Switching MPL" (or "sMPL", see Andersen et al. 2006). This procedure reduces participants' fatigue and produces clean data, but it might have the unintended effect of biasing participants to select a row near the middle and thus exaggerating the compromise effect.

[3] Our procedure differs from T&K's in three ways. First, T&K do not report the actual values they used. Second, while their gambles were all hypothetical, our "Part A" gambles are incentivized. Third, for each screen, T&K

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 its own instruction screen), with each part containing a single type of fixed prospect and a single type of alternative. The order of the screens is randomized within each part, with half the participants completing the screens in one order, and the other half completing 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 alternatives for each fixed prospect range from the fixed prospect's certainty equivalent for a CRRA expected-utility-maximizer with CRRA parameter $\gamma = 0.99$ to the certainty equivalent for $\gamma = -1$ (which is risk seeking).[4] Because the range of estimates of γ in the literature falls well within this interval (Booij, van Praag, and van de Kuilen, 2010), the interval likely covers the relevant range of alternatives for the participants. 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 alternatives are sure losses. The 28 prospects and alternatives 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

implement a two-step procedure: after finding the point at which participants switch from preferring the alternative outcomes to preferring the fixed prospect, 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") to maintain incentive compatibility.

[4] We use $\gamma = 0.99$ because $\gamma = 1$ corresponds to log utility and implies a certainty equivalent of \$0 for any prospect with a chance of a \$0 outcome.

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 prospect and the alternatives are mixed prospects, 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 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	OR	Take gamble 2
(b)	… a 50% chance of gaining \$356.30 instead.	Take gamble 1	OR	Take gamble 2
(c)	… a 50% chance of gaining \$332.50 instead.	Take gamble 1	OR	Take gamble 2
(d)	… a 50% chance of gaining \$302.00 instead.	Take gamble 1	OR	Take gamble 2
(e)	… a 50% chance of gaining \$263.10 instead.	Take gamble 1	OR	Take gamble 2
(f)	… a 50% chance of gaining \$213.40 instead.	Take gamble 1	OR	Take gamble 2
(g)	… a 50% chance of gaining \$150.00 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 prospect 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 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

As detailed below, the experiment has a 5×2 design, with five "Pull" treatments, which vary the set of alternatives, crossed with two "EV" treatments, which vary whether the expected value of the prospects is displayed or not. Each participant is randomly assigned to one of the ten treatment cells and remains in this cell for all screens and all parts (A-D) of the experiment.

The Pull treatments allow us to assess whether the compromise effect impacts measured risk and loss preferences. 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 intermediate (the second through sixth) alternatives. For instance, in Part A for the illustrative fixed prospect above in the screenshots in the Introduction—a 10% chance of gaining \$100 and a 90% chance of gaining \$50—the alternatives (a) through (g) are shown in the positive half of Figure 1 for all five Pull treatments.

The five treatments are labeled Pull -2, Pull -1, Pull 0, Pull 1, and Pull 2. In the Pull 0 treatment, the alternatives 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 intermediate alternatives are more densely concentrated at the monetary amounts closer to zero. These treatments are designed to resemble T&K's experiment, in which the second through sixth alternatives are "logarithmically spaced between the extreme outcomes of the prospect" (T&K, p. 305). Conversely, in the Pull -1 and Pull -2 treatments, the intermediate alternatives are more densely concentrated at the monetary amounts farther 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 intermediate alternatives toward zero (for the positive Pulls) or away from zero (for the negative Pulls).

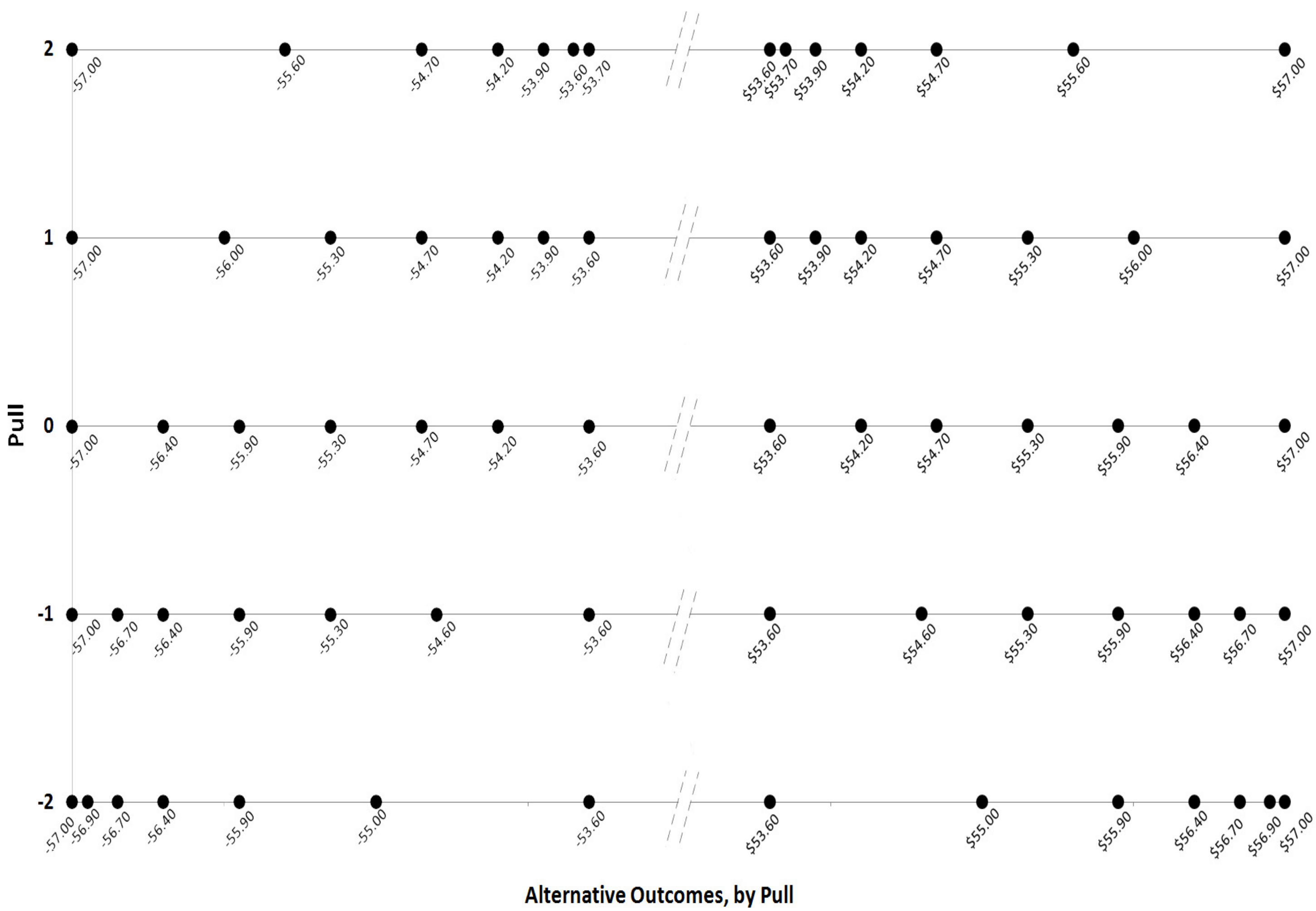

FIGURE 1. Alternative outcomes by Pull treatment for example screens. The right side of the figure shows alternative outcomes by Pull treatment for an example screen from Part A with a fixed prospect offering a 10% chance of gaining $100 and a 90% chance of gaining $50. The left side of the figure shows alternative outcomes by Pull treatment for an example screen from Part B with a fixed prospect offering a 10% chance of losing $100 and a 90% chance of losing $50.

Analogously, in Parts C and D, Pull 1 and Pull 2 pull the distribution of the varying amounts of the intermediate alternative prospect on each screen toward zero, and Pull -1 and Pull -2 do the opposite. The Online Appendix describes the precise algorithm we use to determine the second through sixth alternatives and shows the complete set of fixed prospects and alternatives for each Pull treatment and for each part of the experiment.

The EV treatments differ in whether or not we inform participants about the expected values of the prospects. 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 it. 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."

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 had to be at least 18 years old, eligible to receive payment in the U.S., and not on Harvard University's regular payroll. At the time we ran the experiment, members of the CLER online subject pool database were 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.[5]

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

[5] Participants were allowed to complete the experiment in more than one session and some response times exceeded 24 hours. Of the 497 participants for whom we have response time data, 405 took less than an hour.

experiment.

2.4 Summary Statistics of the Raw Data from the Experiment

Online Appendix Section 3 includes figures that show the percentage of choices where the safe option was chosen, by Pull and EV treatments, separately for Parts A, B, C, and D of the experiment. These figures give a first impression of the data we collected in our experiment, but caution is warranted in interpreting them because the different Pull treatments involve different sets of choices, and the raw data are thus not directly comparable across treatments.

3 Model and Estimation

3.1 Baseline CPT Model

We assume that participants' deep preferences can be modeled according to CPT. For prospect $P = (x_H, p_H; x_L, p_L)$ with probability p_H of monetary outcome x_H and probability $p_L = 1 - p_H$ of monetary outcome x_L, we assume that utility has the 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 $\omega(\cdot)$ is the cumulative probability weighting function and satisfies $\omega(0) = 0$ and $\omega(1) = 1$, $u(\cdot)$ is the Bernoulli utility function and satisfies $u(0) = 0$, and λ is the coefficient of loss aversion. We assume that $u(\cdot)$ takes the CRRA (a.k.a. "power utility") form, $u(x) = \frac{x^{1-\gamma}}{1-\gamma}$, as is standard in the literature on CPT (e.g., Fox and Poldrack 2014; T&K).

We use the Prelec (1998) probability weighting function:

$$\omega(p) = \exp(-\beta(-\log(p))^{\alpha}),$$

where α, $\beta > 0$. The α and β parameters regulate the curvature and the elevation of $\omega(p)$, respectively.

3.2 Modeling the Compromise Effect

We model the compromise effect by assuming that, in addition to their deep CPT preferences, participants suffer a loss in utility from choosing a switchpoint farther from the middle row on the screen. Formally, recall that on each screen q of the experiment, a participant makes choices between a fixed prospect, denoted P_{qf}, and seven alternatives presented in decreasing order of monetary payoff, denoted P_{q1}, P_{q2}, ..., P_{q7}.[6] Following Hey and Orme (1994), we use a Fechner error specification and assume that on any screen q, the participant chooses P_{qi} over P_{qf} if and only if

$$(2) \qquad \frac{U(P_{qi})}{\sigma_q} + c_i + \varepsilon_{qAlt} > \frac{U\left(P_{qf}\right)}{\sigma_q} + \varepsilon_{qf} \quad \Longleftrightarrow \quad \varepsilon_q < \frac{U(P_{qi}) - U\left(P_{qf}\right)}{\sigma_q} + c_i,$$

where c_i is a constant that depends on the row i in which the alternative P_{qi} appears, σ_q is parameter to regulate the relative importance of the utility function vs. the other arguments, and ε_{qf}, ε_{qAlt}, and ε_q are preference shocks that vary across (but not within) screens. We assume that $\varepsilon_{qf} - \varepsilon_{qAlt} \equiv \varepsilon_q \sim N(0,1)$. We refer to c_i as the *parameter for the compromise effect of row* i, and we assume that $\Sigma_{i=1}^{7} c_i = 0$, implying no bias on average toward selecting either the alternative or the fixed prospect. In other words, the constraint implies that this set of parameters does not have an average effect (summing across all rows in the MPL) on the preference between the alternative and the fixed prospect.

Our estimation strategy jointly estimates three sets of parameters: (i) the prospect theory preference parameters for loss aversion, λ, utility curvature, γ, and the form of the probability weighting function, $\{\alpha,\ \beta\}$; (ii) a vector of row-by-row compromise effect parameters, $\{c_i\}_{i=1}^{7}$; and (iii) the scaling parameters, σ_q, that scale utility differences for each screen, q. From our perspective, the scaling parameters are nuisance parameters. The incorporation of the (varying) scaling parameters partially addresses the critique of random utility models identified by Wilcox (2011) and Apesteguia and Ballester (2018). Our use of varying scaling parameters follows the spirit of the recommendations of Wilcox (2011). The solution of Apesteguia and Ballester (2018) – stochastic preferences parameters – could also be incorporated into our framework, though it would involve substantial computational hurdles because we have four preference parameters.

[6] In Part C, the alternative prospects are presented in increasing order of monetary payoff.

3.3 Estimation

We estimate the model via Maximum Likelihood Estimation, pooling participants together and clustering the standard errors at the participant level. We impose the parameter restriction $\gamma < 1$. 15 of the 28 fixed prospects in Part A have a chance of yielding \$0 (and likewise for Part B). Accordingly, $\gamma \geq 1$ would imply that any strictly positive alternative sure outcome would be preferred with probability 1. Every participant in the experiment made choices ruling out such extreme risk aversion, except for one participant.[7]

We simplify the estimation in two ways. First, we reduce the number of σ_q parameters by assuming that σ_q is identical for screens involving prospects of similar magnitudes.[8] Second, we assume that c_i takes the quadratic functional form $c_i = \pi_0 + \pi_1 \cdot i + \pi_2 \cdot i^2$. With this functional form, the constraint $\Sigma_{i=1}^{7} c_i = 0$ implies a linear restriction among the parameters, $\pi_0 = -4\pi_1 - 20\pi_2$, so we estimate the two parameters π_1 and π_2.

For each specification, we produce three sets of estimates. First, we estimate γ, α, and β (and the other parameters) with data from all screens from Parts A-D.[9] To do so, we assume that γ, α, β are the same in the gain and loss domains. Note that γ is then the coefficient of relative risk aversion in the gain domain and the coefficient of relative risk *seeking* in the loss domain. Second, we estimate γ^+, α^+, and β^+ (and the other parameters) with data from Part A only (which only includes questions in the gain domain and is incentivized). Lastly, we estimate γ^-, α^-, and β^- (and the other parameters) with data from Part B only (which only includes questions in the loss domain).

We exclude from the estimation data participants for whom the MLE algorithm does not converge (after 500 iterations) when the CPT model is estimated separately for each participant with data from Parts A-D. We identified 28 such participants out of a total of 521 participants who

[7] As discussed below, we excluded from the estimation participants for whom the MLE did not converge when estimated using only their data. This participant's data were excluded as a result.

[8] For Part A we estimate a σ_q parameter for each of five groups of screens. Screens are grouped together based on the expected utility of their fixed prospects; the latter is calculated based on the parameter estimates reported by Fehr-Duda and Epper (2012, Table 3). We estimate $\sigma_{A,0-25}$, $\sigma_{A,25-50}$, $\sigma_{A,50-75}$, $\sigma_{A,75-100}$, $\sigma_{A,100+}$, where $\sigma_{A,L-H}$ is for screens with a fixed prospect whose expected value is between L and H. For Part B, we proceed analogously. We also estimate $\sigma_{C,\text{small}}$ and $\sigma_{C,\text{big}}$ for the two smaller and the two larger fixed prospects of Part C, respectively, and σ_D for the two fixed prospects of the two screens of Part D we use.

[9] We drop the two screens of Part D that involve only positive outcomes (designed by T&K as placebo tests for loss aversion) so that Parts C and D primarily identify $\hat{\lambda}$. When we refer to "all screens from Parts A-D," we mean all screens excluding these two.

completed all parts of the experiment, and most of them had haphazard response patterns.

To derive a likelihood function, first recall that the experimental procedure constrained participants to behave consistently: if a participant chooses P_{qi} over P_{qf} for some $i > 1$, then the participant chooses P_{qj} over P_{qf} for all $j < i$. Hence the probability that the participant switches from choosing the alternative when the alternative is P_{qi} to choosing the fixed prospect when the alternative is $P_{q(i+1)}$ is

$$\begin{aligned}
\Pr{}_{q,i,i+1} &\equiv \Pr\left(\text{participant switches between } P_{qi} \text{ and } P_{q(i+1)}\right) \\
&= \Pr\left(\frac{U(P_{q(i+1)}) - U(P_{qf})}{\sigma_q} + c_{i+1} < \varepsilon_q < \frac{U(P_{qi}) - U(P_{qf})}{\sigma_q} + c_i\right) \\
&= \Phi\left(\frac{U(P_{qi}) - U(P_{qf})}{\sigma_q} + c_i\right) - \Phi\left(\frac{U(P_{q(i+1)}) - U(P_{qf})}{\sigma_q} + c_{i+1}\right),
\end{aligned}$$

where $\Phi(\cdot)$ is the CDF of a standard normal random variable; the probability that the participant always chooses the fixed prospect is $\Pr{}_{q,-,1} \equiv 1 - \Phi((U(P_{q1}) - U(P_{qf}))/\sigma_q + c_1)$; and the probability that the participant always chooses the alternative over the fixed prospect is $\Pr{}_{q,7,-} \equiv \Phi((U(P_{q7}) - U(P_{qf}))/\sigma_q + c_7)$. We assume that ε_q is drawn *i.i.d.* for each screen q in the set of screens, Q, faced by a participant.

Thus, the likelihood function for any given participant p is:

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

where, for notational simplicity, we write $\Pr_{q,0,1}$ for $\Pr_{q,-,1}$ and $\Pr_{q,7,8}$ for $\Pr_{q,7,-}$. The likelihood function for all the participants pooled together is $\Pi_{p \epsilon P} L_p$, where P is the set of participants.

3.4 Robustness checks

In addition to the baseline CPT model described above (with CRRA utility and the Prelec (1998) probability weighting function), we estimated three additional models: (1) the CPT model with CRRA utility but with T&K's probability weighting function: $\omega(p) = p^\alpha/(p^\alpha + (1-p)^\alpha)^{\frac{1}{\alpha}}$; (2) the CPT model with the Prelec probability weighting function, but with CARA (a.k.a. "exponential") utility (Köbberling and Wakker 2005), $u(x) = \frac{1-e^{-\alpha^+_{\text{expo}} x}}{\alpha^+_{\text{expo}}}$ if $x \geq 0$, $u(-x) = \frac{1-e^{-\alpha^-_{\text{expo}} |x|}}{\alpha^-_{\text{expo}}}$ if $x < 0$; and (3) the CPT model with the Prelec probability weighting function, but with expo-power utility

(Saha 1993), $u(x) = \frac{1-e^{-\alpha_{\text{e-p}} x^{1-\gamma_{\text{e-p}}}}}{\alpha_{\text{e-p}}}$. The results presented below in Sections 5 and 6 are robust to the use of these alternative models (see the Online Appendix for details).

3.5 Identification With and Without the Pull Treatments

Our five Pull treatments are designed to identify the effect of the compromise effect on measured risk preferences. However, even without the Pull treatments, generic risk aversion experiments will be able to identify the compromise effect parameters. To gain intuition for this fact, consider a MPL experiment in which each screen features a different level of risk aversion that elicits indifference at the middle row of the MPL. Accordingly, *measured* risk aversion will vary across screens (unless the researcher takes account of the compromise effect). Hence, the compromise effect will be identified as long as (i) the compromise-effect parameters are included in the model, and (ii) the level of risk aversion that elicits indifference in the middle row varies across MPL screens. Because the compromise effect parameters would be identified even without within-subject variation in the Pull treatment, our data could also be used to identify the compromise effects at the level of each individual participant, but those estimates would be less precise than the representative agent estimates on which we focus in this paper.

4 Hypotheses

Having defined the model, we now articulate a number of hypotheses that we will test empirically by estimating the model with the data from the experiment. Drawing on prior work (see the Introduction for discussion), our starting point is the hypothesis that participants will be biased toward switching close to the middle of the seven rows in the Multiple Price List.

Hypothesis 1: Estimates of c_i will reveal a compromise effect. Specifically, $\hat{c}_i$ will be positive in the top rows, close to zero in the middle rows, and negative in the bottom rows, decreasing monotonically from the first to the last row.

Note that a positive value of c_i implies a bias in favor of choosing the alternative (which is in the right-hand-side column of the MPL), and a negative value of c_i implies a bias in favor of choosing the fixed prospects (which is in the left-hand-side column of the MPL). So Hypothesis 1 implies a switch point that is biased toward the middle row of the MPL.

Thus, the compromise effect implies that measured risk aversion in the gain domain, as assessed in Part A, will be systematically increased across the range of treatments from Pull -2 to Pull 2 (in the model without the compromise effect). For instance, consider the two example screenshots from the Introduction. The first screenshot illustrates the Pull -2 treatment. Since the intermediate alternatives are shifted away from zero, the compromise effect induces participants to choose an indifference point that is farther from zero, thereby implying a relatively low level of risk aversion. In contrast, in the Pull 2 treatment, illustrated in the second screenshot, the intermediate alternatives are shifted closer to zero. The compromise effect causes participants to choose an indifference point that is closer to zero, thereby implying a relatively high level of risk aversion.

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

Similar considerations imply that moving across the range of treatments from Pull -2 to Pull 2 is predicted to reduce the level of estimated loss aversion.

We thus hypothesize that the compromise effect affects estimates of risk aversion and loss aversion in the traditional CPT model. In Section 3.2 above, we introduced a model that incorporates parameters for the compromise effect. If that model is properly specified, we would expect the bias induced by the compromise effect to disappear and the estimates of risk aversion and loss aversion to be similar across Pull treatments. In summary, we hypothesize:

Hypothesis 2.a: Estimates of relative risk aversion in the gain domain (γ, γ^{+}) and relative risk seeking in the loss domain (γ, γ^{-}) from our model with the compromise effect will not vary in Pull.

Hypothesis 2.b: Estimates of loss aversion (λ) from our model with the compromise effect will not vary in Pull.

Hypothesis 3.a: Estimates of γ, γ^+, and γ^- from the model *without* the compromise effect will be increasing in Pull.

Hypothesis 3.b: Estimates of λ from the model *without* the compromise effect will be decreasing in Pull.

5 Estimating the Compromise Effect and Risk Preferences Jointly

We begin by estimating our model with the compromise effect. We focus our attention on the curvature parameter γ and the loss aversion parameter λ because our ex ante hypotheses are about these parameters. We do not interpret the results for the other parameters (α, β, and the σ_q parameters) because we did not have ex ante hypotheses, but we report the estimates for all parameters in the Online Appendix.

Table 1 shows the estimates for our parameters of interest. The estimates of γ (obtained from the data from all parts together), γ^+ (obtained from the data from Part A only), and γ^- (obtained from the data from Part B only) differ substantially from one another, ranging from $\hat{\gamma}^- = -0.106$ to $\hat{\gamma}^+ = 0.448$. The estimate of γ^- is significantly smaller than 0 at the 5% level, indicating risk *aversion* in the loss domain, which is the opposite of what CPT predicts. The estimate of λ (obtained from the data from all parts together) is 1.311, consistent with some loss aversion, albeit less than usually assumed. Except for the notably small estimate of γ^-, our parameter estimates (including those for the probability weighting function parameters) are broadly in line with existing estimates in the literature. We compare our estimates to the literature in Section 10.

<INSERT TABLE 1 ABOUT HERE>

The sizeable difference between the estimates in Parts A and B suggests that the assumption that γ, α, and β are the same in the gain and loss domains is unsupported by the data. We nonetheless maintain this assumption when estimating the model with the data from all parts of the experiment because we are interested in studying $\hat{\lambda}$, and as Wakker (2010) points out, assuming different parameters in the gain and loss domains makes the loss aversion parameter more difficult to interpret.[10]

5.1 Estimating the Compromise Effect

We now proceed to test *Hypothesis 1*, which predicts that the parameters for the compromise effect c_i will be positive in the top rows, close to zero in the middle rows, and negative in the bottom rows, and will decrease from the first to the last row.

The estimated c_i's are calculated from the estimates of π_1 and π_2. Figure 2 shows the estimated c_i for each row i (the numerical values are listed in the Online Appendix). As can be seen, the estimated c_i's decline from row 1 (where c_1 is large and positive) to row 7 (where c_7 is large and negative), and c_4 is always relatively small (in fact, it is not significantly different from 0 at the 5% level when estimated with the data from Part A or Part B only). These results indicate that participants tend to switch from choosing the alternative to choosing the fixed prospect toward the middle row. Furthermore, the estimates of the π_1 and π_2 parameters reported in Table 1 are highly jointly statistically distinguishable from zero: the p-value of the Wald test is less than 1×10^{-10}. These results strongly support Hypothesis 1 and are robust to restricting the data to the incentivized Part A only. We note that the compromise effect is weaker when estimated with the data from Part A versus the data from Part B. This may suggest that the compromise effect is stronger in the loss domain; alternatively, participant fatigue and the lack of incentives in Part B could have led to reduced participant attention and to a stronger compromise effect.

[10] Wakker (2010, section 9.6) highlights two concerns when $u(\cdot)$ takes the CRRA form and $\gamma^+ \neq \gamma^-$. 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 make estimates of λ sensitive to exactly which prospects are used in the experiment. As previously mentioned, in the Online Appendix we report estimates of a robustness check where we assume CARA utility and different risk aversion parameters in the gain and loss domains.

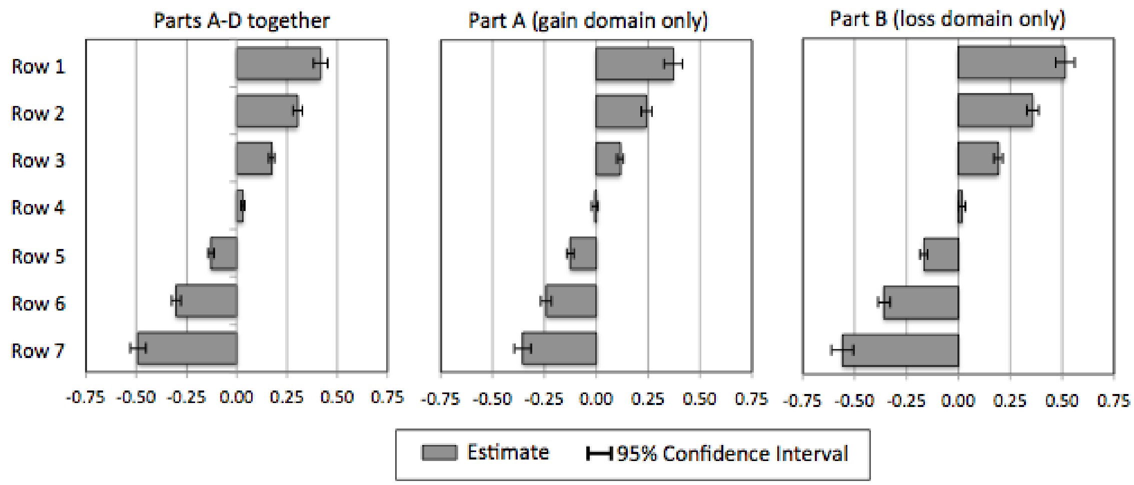

FIGURE 2. Implied estimates of the parameters for the compromise effect c_i as a function of the row i in which a choice appears. In the estimation, we parameterize the parameters for the compromise effect with the quadratic functional form $c_i = \pi_0 + \pi_1 \cdot i + \pi_2 \cdot i^2$, $\Sigma_{i=1}^{7} c_i = 0$, which is equivalent to $c_i = \pi_1 \cdot (i-4) + \pi_2 \cdot (i^2 - 20)$. Note that the confidence intervals are smaller around the middle rows because $var(\hat{c}_i) \approx (i-4)^2 var(\hat{\pi}_1) + (i^2-20)^2 var(\hat{\pi}_2)$ (assuming $cov(\hat{\pi}_1, \hat{\pi}_2) \approx 0$).

5.2 Robustness of the Preference-Parameter Estimates from Joint Estimation

To test Hypotheses 2a and 2b, we begin by estimating the model with the compromise effect separately in the subsamples corresponding to each of the five Pull treatments. Figure 3 shows estimates of γ, γ^+ and γ^-, with 95% confidence intervals, for each subsample. Figure 4 shows estimates of λ.

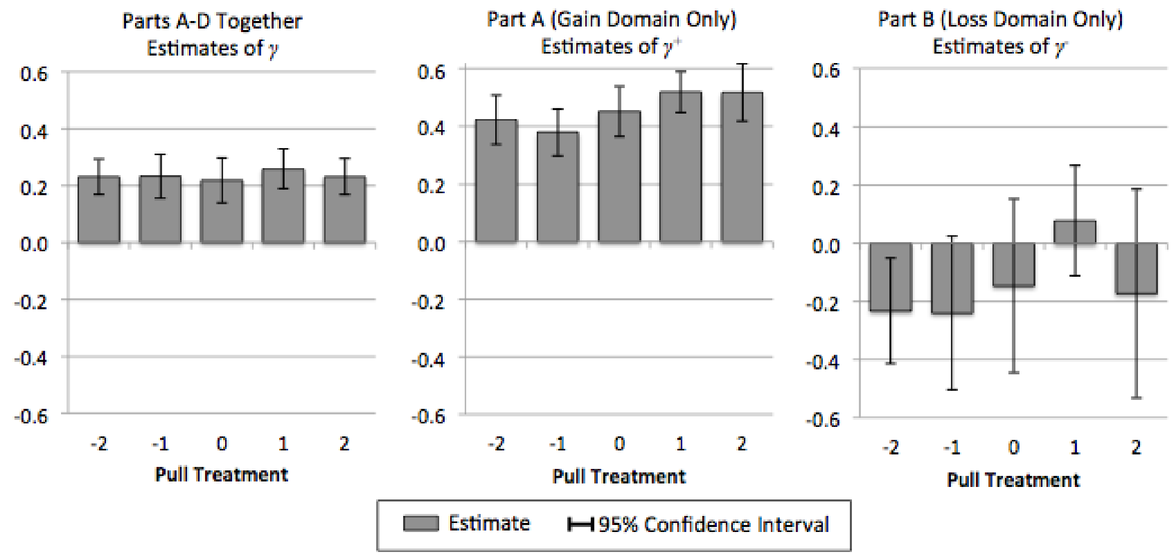

FIGURE 3. Estimates of γ, γ^{+}, and γ^{-} by Pull treatment, from the model with the compromise effect. The negative estimates of γ^{-} for Part B reflect risk aversion in the loss domain, unlike what CPT predicts. (γ is not estimated for Parts C and D only because these parts have few questions.)

As can be seen, the estimates of γ, γ^{+}, γ^{-}, and λ do not differ substantially across Pull treatments, consistent with Hypotheses 2a and 2b. To formally test for equality across treatments, we estimate the model with all parameters specified as linear functions of the Pull variable and of a dummy that indicates if the participant was in the EV treatment. In other words, we substitute γ in the utility function in (1) by $\gamma = \gamma_0 + \phi_1^{\gamma} \cdot Pull + \phi_2^{\gamma} \cdot EV$, λ by $\lambda = \lambda_0 + \phi_1^{\lambda} \cdot Pull + \phi_2^{\lambda} \cdot EV$, and do likewise for α, β, and all the σ_q parameters, and we test whether the ϕ parameters are equal to zero.[11]

[11] The statistical power to test the pairwise differences in our parameter estimates (for each discrete step in the Pull treatment) is limited. Accordingly, we test *Hypothesis* 3.a and *Hypothesis* 3.b by estimating a linear model. Figures 5 and 6 imply that a linear specification is a good approximation.

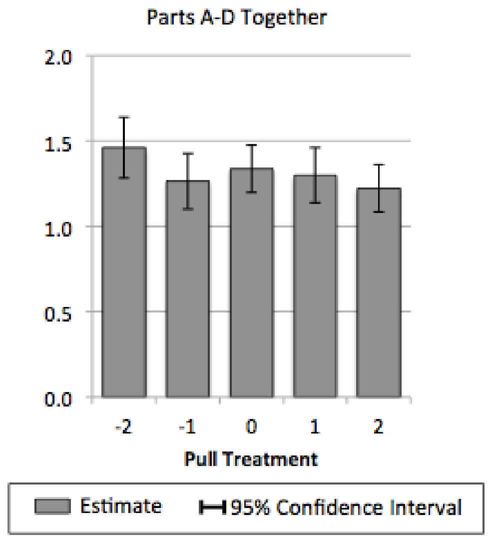

FIGURE 4. Estimates of λ by Pull treatment from the model with the compromise effect, for Parts A-D together. (λ cannot be estimated for Part A only or Part B only because the questions in these parts are all in the gain or loss domains. We do not estimate λ for Parts C and D only because these parts have few questions.)

Table 2 shows the results. The three estimates of ϕ_1^γ are all close to zero, and none is statistically distinguishable from zero (including the estimate from the incentivized Part A). We interpret these estimates as providing more formal support for Hypothesis 2a. The estimate of ϕ_1^λ is significantly different from zero at the 10% level, and its sign is consistent with what one would expect from the Pull manipulation, which suggests that our model with the compromise effect does not perfectly control for this effect. As we will see below, however, this estimate of ϕ_1^λ is much smaller than the one obtained from the model without the compromise effect, indicating that our model with the compromise effect substantially reduces the bias due to this effect.

<INSERT TABLE 2 ABOUT HERE>

Taken together, we interpret the evidence as strongly supportive of Hypothesis 2a and also broadly supportive of Hypothesis 2b. In other words, our model (2) yields robust estimates of the CPT parameters γ and λ, both when estimated in the sample of all participants and within the subsamples corresponding to each of the five Pull treatments.

6 Biases in Estimated Risk Preferences when the Compromise Effect Is Omitted from the Model

We now proceed to estimate the CPT model without the compromise effect, the version of the model usually estimated by economists. As above, we focus our attention on γ and λ; results for all parameters are presented in the Online Appendix.

Table 3 shows the estimates for selected parameters. The estimates of γ, γ^+ and γ^- are all smaller in magnitude than those from the model with the compromise effect (2), indicating less curvature in the utility function. The estimate of γ^- is not significantly different from 0 anymore, consistent with a linear utility function in the loss domain. The estimate of λ is not significantly different from its value when estimated in the model with the compromise effect.

<INSERT TABLE 3 ABOUT HERE>

The parameter estimates all fall within the range of existing estimates in the literature (except for $\hat{\beta}^+$, which falls slightly below the range).

To test Hypotheses 3a and 3b, we proceed analogously as above and estimate the model without the compromise effect separately in the subsamples corresponding to each of the five Pull treatments. As can be seen from Figures 5 and 6, the estimates differ substantially across Pull treatments. As predicted by Hypotheses 3a and 3b, $\hat{\gamma}$, $\hat{\gamma}^+$ and $\hat{\gamma}^-$ are increasing in Pull and $\hat{\lambda}$ is decreasing in Pull. Comparing Figures 5 and 6 to Figures 3 and 4, it is clear that failing to control for the compromise effect when estimating the model separately for each treatment introduces a sizeable bias in the estimates of γ and λ.

As can be seen in the right panel of Figure 5, the Pull treatment manipulation of the compromise effect is strong enough to generate estimates of γ^- that are either significantly smaller than 0 (Pull -2) or significantly larger than 0 (Pull 2). Furthermore, as can be seen from Figure 6, the Pull treatment manipulation of the compromise effect causes estimates of λ to vary from 1.059 (Pull 2) to 1.746 (Pull -2). The former estimate is not significantly different from 1 at the 10% level, suggesting that the compromise effect can create the appearance of no loss aversion.

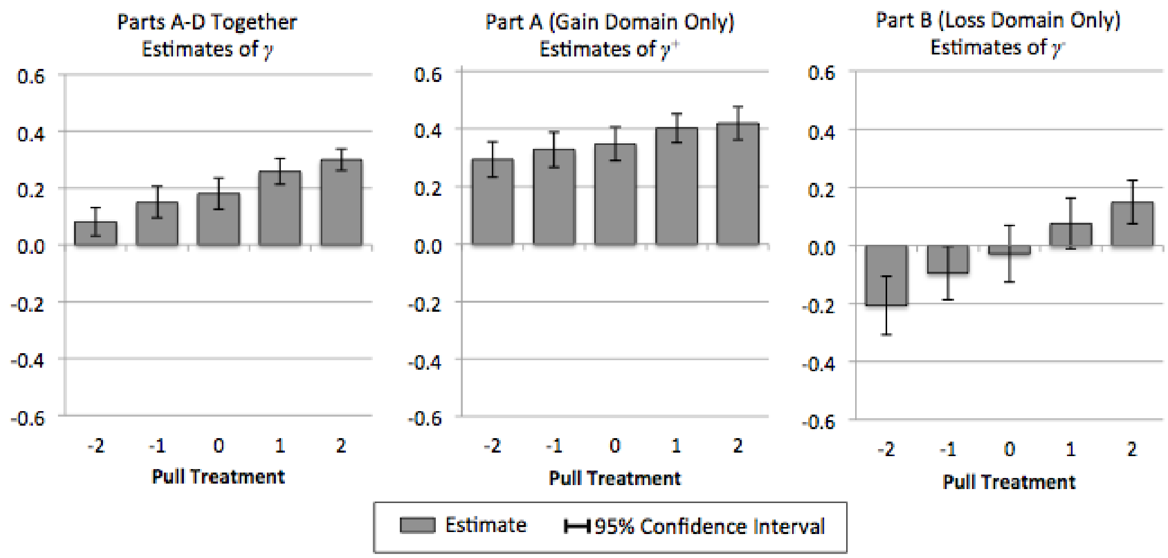

FIGURE 5. Estimates of γ, γ^+, and γ^- by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 3, except that the estimated model does not control for the compromise effect.

As above, we formally test the impact of the compromise effect by specifying all parameters as linear functions of the Pull variable and of a dummy that indicates if the participant was in the EV treatment. The results are presented in Table 4. $\hat{\phi}_1^{\gamma}$ is significant at the 1% level and positive in all three columns (including in the column corresponding to the incentivized Part A), providing formal support for Hypothesis 3a. The implied differences between the estimates in the Pull -2 and the Pull 2 treatments are sizeable: for $\hat{\gamma}$, the implied difference is 0.168 (4×0.042), and for $\hat{\gamma}^-$, the corresponding figure is 0.252 (4×0.063). $\hat{\phi}_1^{\lambda}$ is highly statistically significant and negative, thus supporting Hypothesis 3b. The implied difference between $\hat{\lambda}$ in the Pull -2 and the Pull 2 treatments is 0.588 (4×0.147).

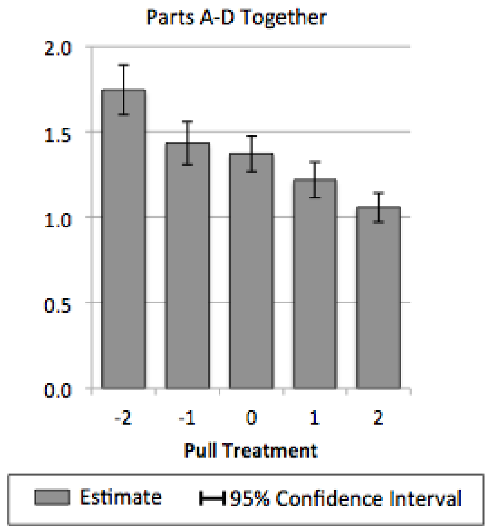

FIGURE 6. Estimates of λ by Pull treatment from the model without the compromise effect, for Parts A-D together. This figure is analogous to Figure 4, except that the estimated model does not control for the compromise effect.

<INSERT TABLE 4 ABOUT HERE>

The evidence thus strongly supports Hypotheses 3a and 3b and suggests that many existing results based on experiments using the MPL elicitation method may be severely biased due to the compromise effect.

7 How Large is the Compromise Effect?

Having demonstrated that the compromise effect can have a significant impact on choice in a MPL setting, we now obtain a rough estimate of its importance relative to the prospects' monetary outcomes.

To do so, we make an assumption that we show in the next paragraph is justified empirically: the magnitude of the compromise effect and of the preference shocks scales linearly with the expected utilities of the prospects on a screen. Formally, we assume that there is a constant $\Delta > 0$ such that for all screens q,

$$\sigma_q = \Delta \cdot |U(P_{qf})|, \tag{3}$$

where the parameter σ_q (as defined in Section 3.2) regulates the relative importance of utility vs. the other parameters for the compromise effect and shocks, and $U(P_{qf})$ is the expected utility of the fixed prospect on screen q. Thus, for the prospects from Part A (which are all in the gain domain, allowing us to ignore the absolute value sign), we can substitute $\Delta \cdot U(P_{qf})$ for σ_q in Equation (2) of our model. It follows that a participant will prefer the alternative P_{qi} over the fixed prospect P_{qf} in row i of screen q if and only if

$$\begin{aligned} & U(P_{qi}) - U(P_{qf}) + \Delta \cdot c_i \cdot U(P_{qf}) > \sigma_q \varepsilon_q \\ \iff \quad & U(P_{qi}) - U\left((1+\theta_i) \cdot P_{qf}\right) > \sigma_q \varepsilon_q, \end{aligned}$$

where $(1+\theta_i) = (1-\Delta c_i)^{\frac{1}{1-\gamma}}$. For the prospects from Part B, a similar equivalence holds, but with $(1+\theta_i) = (1+\Delta c_i)^{\frac{1}{1-\gamma}}$. Therefore, our assumption enables us to quantify the influence of a compromise effect c_i as the factor $(1+\theta_i)$ by which the screen's fixed prospect would have to be multiplied to have the same effect on choice. Equivalently, θ_i is the magnitude of the compromise effect measured in terms of a fraction of monetary value of the screen's fixed prospect (with a negative value meaning that the compromise effect makes the fixed prospect less likely to be chosen).

We now assess our assumption in equation (3) empirically. Recall from Section 3.3 that, to estimate our models, we group screens together that have similar expected values of their fixed prospects and estimate a common $\hat{\sigma}_q$ for each group. Defining (and slightly abusing) some notation, let $\hat{U}(P_{\tilde{q}f})$ denote the expected utility of the fixed prospect on screen $\tilde{q}$ calculated using the model parameters estimated from the specification with the compromise effect; and let $\hat{E}_{\tilde{q}\in q}[|\hat{U}(P_{\tilde{q}f})|]$ denote the mean of the absolute values of these $\hat{U}(P_{\tilde{q}f})$'s across all the screens $\tilde{q}$ in group q. (Because the screens in a group have similar $\hat{U}(P_{\tilde{q}f})$'s, each $\hat{U}(P_{\tilde{q}f})$ has roughly the same magnitude as the group mean.) The empirical counterpart to equation (3) would be a multiplicative relationship between $\hat{\sigma}_q$ and $\hat{E}_{\tilde{q}\in q}[|\hat{U}(P_{\tilde{q}f})|]$ that is the same across different groups q. Figure 7 illustrates this relationship in our data. As can be seen, for the three sets of estimation results (Parts A-D together, Part A, and Part B), $\hat{\sigma}_q$ indeed appears to be reasonably well approximated as a multiplicative constant times $\hat{E}_{\tilde{q}\in q}[|\hat{U}(P_{\tilde{q}f})|]$. Moreover, the multiplicative constant $\hat{\Delta}$ is nearly the same across the three sets of results, ranging from 0.32 to 0.36.[12]

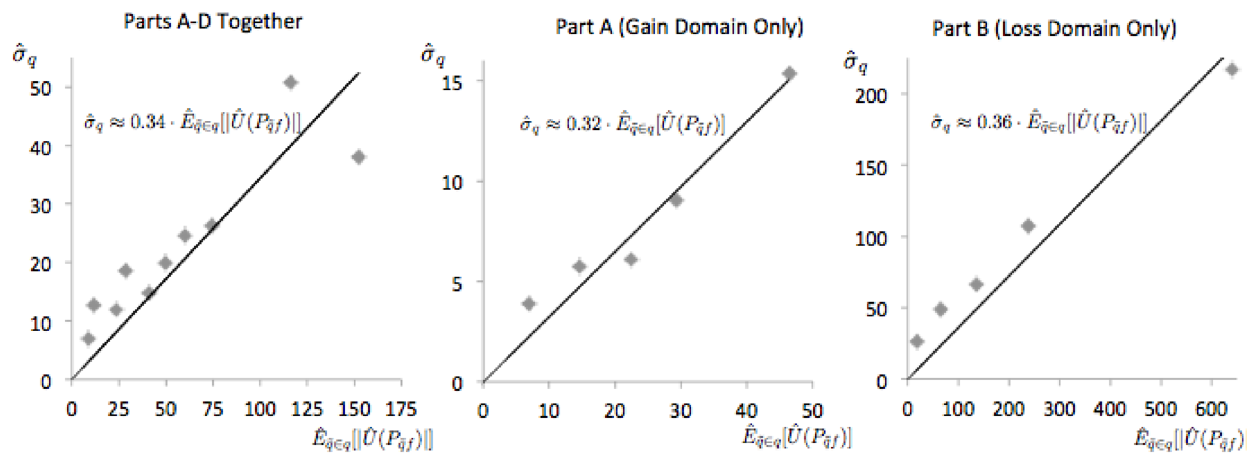

FIGURE 7. Relationship between $\hat{\sigma}_q$ and the expected utility of a screen's fixed prospect. See text for details.

Using the estimated $\hat{\Delta}$ for each of the three sets of results, Table 5 presents estimates of the strength of the compromise effect, $\hat{\theta}_i$, for each row i on a screen (because this is meant to be an approximation, we omit standard errors).

<INSERT TABLE 5 ABOUT HERE>

Our estimates of the strength of the compromise effect in a screen's first and last rows (where their impact is largest) range in magnitude from ∼17% to ∼23% of the monetary value of the screen's fixed prospect. We interpret such magnitudes as non-trivial.

[12] In OLS regressions of $\hat{\sigma}_q$ on a constant and $\hat{E}_{\tilde{q}\in q}[|\hat{U}(P_{\tilde{q}f})|]$, the intercept is economically small in all cases. For the estimates of $\hat{\Delta}$ reported here, we use a 0 intercept.

8 Demographic Correlates of the CPT Model Parameters and of the Parameters that Capture the Compromise Effect

A large literature seeks to estimate the demographic correlates of economic preferences and decision making (e.g., Beauchamp, Cesarini, and Johannesson 2017, Benjamin, Brown, and Shapiro 2013, Booij, van Praag, and van de Kuilen 2010, Dohmen, Falk, Huffman, and Sunde 2010). The data we collected in our experiment, which include a number of demographic variables, allow us to contribute to this literature by analyzing the demographic correlates of the four key parameters of the CPT model (γ, λ, α, β) and of the two model parameters that capture the compromise effect (π_1, π_2). In our baseline demographic specification, we estimate our CPT model with the compromise effect using data from Parts A-D together, with these six key model parameters specified as linear functions of a constant, age, sex, a dummy variable indicating whether one has a college degree, SAT Math score, the log of one's parents' combined annual income, as well as dummy variables to control for race. We also estimated several additional specifications to verify the robustness of the results from our baseline demographic specification. First, we estimated the baseline demographic specification again, but using data from Part A only, and then using data from Part B only. Second, we estimated a specification akin to the baseline demographic specification using data from Parts A-D together, but with CARA (a.k.a. "exponential") utility (Köbberling and Wakker 2005). Lastly, we employed a two-step procedure in which we first estimated our baseline CPT model with the compromise effect separately for each participant, and then regressed each estimated parameter of interest on the demographic variables. To reduce the number of parameters and thereby improve the frequency of convergence in the first step of that procedure, we assume that σ_q is identical across all screens (for each experimental participant).

Two main results stand out across the baseline and robustness specifications. First, higher SAT Math scores are associated with lower γ—i.e., with lower risk aversion in the gain domain and higher risk aversion (or, equivalently, lower risk seeking) in the loss domain. This result is consistent with the existing literature on the association between cognitive ability and risk preferences (see Dohmen, Falk, Huffman, and Sunde 2018 for a review of the literature), although it has been argued that this association is driven by the fact that measurement noise may be higher for individuals with lower cognitive ability (Andersson, Holm, Tyran, and Wengström 2016). The second result that stands out is that higher SAT Math scores are associated with *higher* loss aversion (λ). This result, although robust across our specifications, is surprising given that previous research has found that education is negatively associated with loss aversion (Booij, van Praag, and van de Kuilen 2010, Gächter, Johnson, Herrmann 2007, Hjorth and Fosgerau 2011). Aside from these two results, the associations between the other covariates and parameters were not statistically distinguishable from zero or were not robust across specifications.

The Online Appendix reports estimates of the baseline demographic specification and provides additional details. We note that one limitation of this analysis is that our sample of experimental participants was not selected to be representative of the population.

9 Effect of Displaying the Gambles' Expected Values on Estimated Risk Preferences

Displaying the expected value may anchor the participants on the expected value (Tversky and Kahneman, 1974) or simplify comprehension of the gamble (Benjamin, Brown, and Shapiro, 2013), thereby making observed preferences more risk neutral. We therefore hypothesize that (1) $\hat{\gamma}^+$ and $\hat{\gamma}^-$ will shift toward 0 in the EV treatment, and (2) $\hat{\lambda}$ will shift toward 1 in the EV treatment.

Online Appendix Figures 1-4 show estimates of $\hat{\gamma}$ and $\hat{\lambda}$ for the subsamples corresponding to the two EV treatments, with 95% confidence intervals. Displaying the expected value does not appear to affect estimated risk preferences or loss aversion. In addition, none of the estimates of $\hat{\phi}_2^{\gamma}$ and of $\hat{\phi}_2^{\lambda}$ in Table 4 are statistically distinguishable from zero. Thus, like Lichtenstein, Slovic, and Zink (1969) and Montgomery and Adelbratt (1982) but unlike Harrison and Rutström (2008), we do not find support for the hypothesis that the EV treatment shifts $\hat{\gamma}^+$ and $\hat{\gamma}^-$ toward 0 and $\hat{\lambda}$ toward 1. A difference between our experiment and Harrison and Rutström's (2008) is that the prospects in the latter are more complex, involving four possible outcomes. It is possible that participants intuitively estimate the prospects' expected values in our experiment but are not able to accurately do so in Harrison and Rutström's experiment, and that providing expected value information is therefore redundant in our experiment but not in theirs.

10 Conclusion

In this paper, we estimate an econometric model that explicitly takes into account the compromise effect and thus disentangles it from risk preference parameters. The resulting risk-preference estimates are robust: the inferred risk parameters essentially do not change with exogenous manipulations of the compromise effect. Without parameters for the compromise effect, however, we replicate the finding from prior work that risk-preference estimates are sensitive to exogenous manipulations of the compromise effect.

How do our "debiased" preference-parameter estimates (from Table 1) compare to those from the literature? For risk aversion in the gain and loss domains, we estimate $\hat{\gamma}^{+} = 0.448$ and $\hat{\gamma}^{-} = -0.106$, respectively. Booij, van Praag, and van de Kuilen's (2010) Table 1 reviews existing experimental estimates. Translated into the CRRA functional form we estimate, the range of existing parameter estimates is $\hat{\gamma}^{+} \in [-0.01, 0.78]$ in the gain domain and $\hat{\gamma}^{-} \in [-0.06, 0.39]$ in the loss domain. For loss aversion, we estimate $\widehat{\lambda} = 1.311$. Although T&K estimated λ to be 2.25, the literature contains a broad range of estimates: among the papers reviewed by Abdellaoui, Bleichrodt, and Paraschiv (2007, Tables 1 and 5), $\hat{\lambda} \in [0.74, 8.27]$, and among those reviewed by Booij, van Praag, and van de Kuilen (2010, Table 1), $\hat{\lambda} \in [1.07, 2.61]$. Finally, our estimates of the two-parameter Prelec (1998) probability-weighting parameters are in the ranges $\widehat{\alpha} \in [0.564, 0.690]$ and $\widehat{\beta} \in [0.858, 1.471]$. Booij, van Praag, and van de Kuilen's (2010) Table 1 only lists three studies that estimated this 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 $\hat{\beta}^{+} \in [1.08, 2.12]$. Fox and Poldrack's (2014) Table A.3 also lists three studies that estimated the two-parameter Prelec (1998) functional form for prospects in the gain domain. The ranges of estimates are $\hat{\alpha}^{+} \in [0.62, 1.15]$ and $\hat{\beta}^{+} \in [1.00, 1.58]$. Overall, then, our parameter estimates are broadly in line with existing estimates in the literature, except that some of our estimates of the probability weighting parameter β^{+} and our estimate of risk aversion in the loss domain γ^{-} fall below the range of estimates in the literature—indeed, our estimate of γ^{-} indicates risk *aversion* in the loss domain, the opposite of CPT's prediction.

As in T&K, 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. Could a version of prospect theory in which the reference point reflects a participant's expectations explain why the manipulations of the choice set influence the estimated preference parameters (when we do not include parameters for the compromise effect)? This question poses a challenging research program. Modeling the reference point as an expectation would not merely make the reference point depend on the alternative options in the current choice problem but also on the sequence of choice problems that have been faced already, as well as the experimental instructions. Existing work provides little guidance on modeling these complex relationships, and many ad hoc assumptions would be needed.[13]

A limitation of our paper is that the compromise-effect parameter values we estimate are specific to our experimental setting, and thus cannot be extrapolated to other settings (see related points in Levitt and List 2007). For example, our experiment includes 64 MPL's, which may induce fatigue among experimental participants, potentially explaining why the compromise effect strengthens from Part A to Part B. However, the methodology we demonstrate—jointly estimating the compromise effect and preference parameters—is general and can be applied and extended in at least three useful directions.

First, the compromise-effect controls that we propose here can be used not only to improve the robustness of estimates of risk preference parameters, but also of parameter estimates for any other preferences elicited using MPLs, including time and other-regarding preferences. Second, our method can be applied to other settings where the compromise effect may play a role, such as Choi, Fisman, Gale, and Kariv's (2007) graphical interface for eliciting preferences, Andreoni and Sprenger's (2012) convex time budget procedure for eliciting time preferences, or consumer choices in the kinds of settings that originally motivated the psychology and marketing research on the compromise effect (Simonson 1989). Finally, the same econometric procedure we implement here—estimating a discrete-choice model that includes additional parameters that capture location in the choice set—could also be applied to measure and control for other types of context effects, such as a tendency to choose items that happen to come at the beginning of a list of alternatives (e.g., as in election ballots; e.g., Koppell and Steen 2004).

[13] Sprenger (2015) assumes that the fixed prospect in each binary choice pins down a participant's reference point. Because the fixed prospect was held constant across our scale manipulations, this approach can't explain the effects we find.

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Table 1. ML Estimates of Selected Parameters in the Model with the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
γ, γ^{+}, γ^{-}	0.242***	0.448***	-0.106**
	(0.016)	(0.020)	(0.043)
λ	1.311***		
	(0.034)		
α, α^{+}, α^{-}	0.619***	0.564***	0.690***
	(0.015)	(0.015)	(0.022)
β, β^{+}, β^{-}	1.119***	0.858***	1.471***
	(0.025)	(0.033)	(0.061)
π_1	-0.091***	-0.134***	-0.144***
	(0.012)	(0.018)	(0.018)
π_2	-0.008***	0.002	-0.004*
	(0.001)	(0.002)	(0.002)
Log-likelihood	-55,379	-23,915	-25,400
Wald test for π_1, π_2	$p < 1 \times 10^{-10}$	$p < 1 \times 10^{-10}$	$p < 1 \times 10^{-10}$
Parameters	19	10	10
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level. These are tests of the null hypothesis that the coefficient is zero. However, with respect to all parameters (except π_1 and π_2) the natural null hypothesis is not equality to 0. For instance, λ is the loss aversion parameter, so the hypothesis of local linearity is $\lambda = 1$. We reject this restriction: the t-stat is $(1.311 - 1)/0.034 = 9.15$.

Table 2. ML Estimates of Selected Parameters in the Parameterized Model with the Compromise Effect

		Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
γ, γ^+, γ^-	γ_0	0.206***	0.423***	-0.118**
		(0.026)	(0.028)	(0.052)
	ϕ_1^γ	0.008	0.011	-0.032
		(0.017)	(0.018)	(0.026)
	ϕ_2^γ	0.058*	0.033	0.002
		(0.035)	(0.039)	(0.067)
λ	λ_0	1.271***		
		(0.053)		
	ϕ_1^λ	-0.053*		
		(0.029)		
	ϕ_2^λ	0.075		
		(0.074)		
α, α^+, α^-	α_0	0.556***	0.505***	0.617***
		(0.019)	(0.018)	(0.027)
β, β^+, β^-	β_0	1.190***	0.911***	1.524***
		(0.037)	(0.048)	(0.086)
π_1		-0.090***	-0.139***	-0.142***
		(0.012)	(0.018)	(0.018)
π_2		-0.008***	0.002	-0.005**
		(0.001)	(0.002)	(0.002)
Log-likelihood		-55,225	-23,839	-25,343
Wald test for π_1, π_2		$p < 1 \times 10^{-10}$	$p < 1 \times 10^{-10}$	$p < 1 \times 10^{-10}$
Parameters		53	26	26
Individuals		493	493	493
Observations		30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level. These are tests of the null hypothesis that the coefficient is zero.

Table 3. ML Estimates of Selected Parameters in Model Without the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
γ, γ^{+}, γ^{-}	0.203***	0.363***	-0.010
	(0.012)	(0.014)	(0.022)
λ	1.337***		
	(0.027)		
α, α^{+}, α^{-}	0.574***	0.538***	0.615***
	(0.010)	(0.011)	(0.013)
β, β^{+}, β^{-}	1.123***	0.958***	1.296***
	(0.016)	(0.020)	(0.030)
Log-likelihood	-59,957	-25,604	-28,141
Parameters	17	8	8
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering.

* significant at 10% level; ** significant at 5% level; *** significant at 1% level. These are tests of the null hypothesis that the coefficient is zero.

Table 4. ML Estimates of Selected Parameters in the Parameterized Model Without the Compromise Effect

		Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
γ, γ^+, γ^-	γ_0	0.196***	0.353***	-0.003
		(0.016)	(0.018)	(0.026)
	ϕ_1^γ	0.042***	0.041***	0.063***
		(0.009)	(0.012)	(0.012)
	ϕ_2^γ	0.001	0.003	-0.022
		(0.023)	(0.029)	(0.030)
λ	λ_0	1.318***		
		(0.040)		
	ϕ_1^λ	-0.147***		
		(0.022)		
	ϕ_2^λ	0.086		
		(0.059)		
α, α^+, α^-	α_0	0.535***	0.497***	0.577***
		(0.012)	(0.014)	(0.016)
β, β^+, β^-	β_0	1.143***	0.980***	1.305***
		(0.022)	(0.028)	(0.037)
Log-likelihood		-59,427	-25,406	-27,852
Parameters		51	24	24
Individuals		493	493	493
Observations		30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level. These are tests of the null hypothesis that the coefficient is zero.

Table 5. Implied Impact of the Compromise Effect Expressed as a Fraction of the Monetary Value of a Screen's Fixed Prospect ($\hat{\theta}_i$)

	Parts A-D Together		Part A (Gain	Part B (Loss
	Prospects from Part A	Prospects from Part B	Domain Only)	Domain only)
Row 1	-0.18	0.19	-0.20	0.17
Row 2	-0.13	0.14	-0.14	0.12
Row 3	-0.08	0.08	-0.07	0.06
Row 4	-0.01	0.01	0.00	0.01
Row 5	0.06	-0.06	0.07	-0.05
Row 6	0.14	-0.13	0.14	-0.12
Row 7	0.23	-0.21	0.22	-0.18

NOTE: As explained in the text, these figures are approximate.

12 APPENDIX: Screenshots of the Experiment

Screenshots of a randomly selected screen from each part of the experiment are shown below for a participant in the Pull -1 and EV treatments. 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

for

Controlling for the Compromise Effect Debiases Estimates of Risk Preference Parameters

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Contents

1 Complete Set of Fixed Prospects and Alternatives for Each Pull Treatment and Part of the Experiment

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 1.1 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 1.2 lists the fixed prospects and the unfixed parts of the alternative prospects for Parts C and D.

Online Appendix Table 1.1: 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
	EU[t]	9.7	15.9	23.9	15.2	22.4	28.8	36.3	47.3	21.0	31.9	52.2	78.6	97.0	38.0	175.9	41.3	46.4	52.9	46.6	52.8	58.3	64.8	74.4	73.0	78.8	84.0	90.1	99.1
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. The 28 prospects and alternatives in Part B are identical to those in Part A but with all dollar amounts multiplied by -1.

[t] EU refers to the expected utility of the fixed prospects, calculated with the parameter estimates reported by Fehr-Duda and Epper (2012, Table 3) for their representative sample. (In the estimation of the CPT model (with or without compromise effects), one σ_q is estimated for each group of screens and the screens are grouped together based on the expected value of their fixed prospects.)

Online Appendix Table 1.2: 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.

2 Algorithm to Determine the Second Through Sixth Alternatives for Each Pull Treatment and Part of the Experiment

As described in the paper, the Pull 1 and Pull 2 treatments are designed to resemble T&K's experiment, in which the second through sixth alternatives are "logarithmically spaced between the extreme outcomes of the prospect" (T&K, p. 305). Conversely, in the Pull -1 and Pull -2 treatments, the alternatives are more densely concentrated at the monetary amounts farther from zero. Pull 2 and Pull -2 are more skewed than Pull 1 and Pull -1.

We use the following algorithm to determine the second through sixth alternative outcomes for screen q in Pull 1 and Pull 2 for Part A (in the gain domain):

· Label the alternative outcomes for screen q, in decreasing monetary amounts, x_{q1}, x_{q2},...,x_{q7} and define $\Delta_q \equiv x_{q1} - x_{q7}$.

· Recall that (as described in the paper) x_{q1} and x_{q7} (the first and seventh alternatives of screen q) are identical across treatments and correspond to the screen's fixed prospect's certainty equivalents for CRRA expected-utility-maximizers with CRRA parameters $\gamma = -1$ and $\gamma = 0.99$.

· For Pull 1, let $k = 0.3$ and solve $(1+a)^6 k\Delta_q = (1+k)\Delta_q$ for a. Then, let $z_i = (1+a)^{(7-i)} k\Delta_q$, $i = 1, ..., 7$. These seven z_i points form a log scale from $k\Delta_q$ to $(1+k)\Delta_q$.

· We then "shift" the log scale formed by these z_i points so that the scale starts at x_{q7} and ends at x_{q1}: $x_{qi} = z_i + (x_{q7} - k\Delta_q)$, $i = 2, ..., 6$, and round to the nearest dime.

· The algorithm for Pull 2 is identical, except that we let $k = 0.05$.

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.

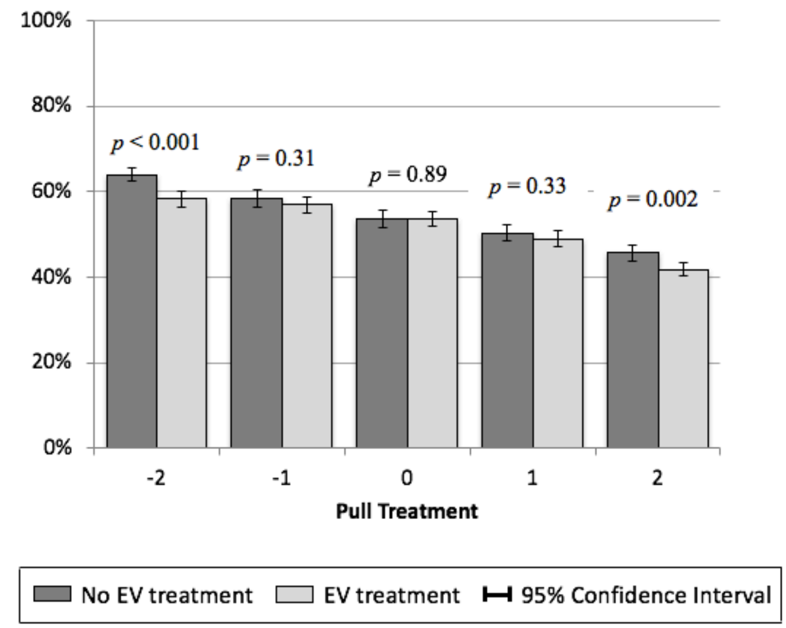
The amounts for Part B are identical to the amounts for Part A, multiplied by -1.

For Parts C and D, we use the same algorithm to determine the parts of the second through sixth alternatives that are not fixed. (Recall that the alternatives in Parts C and D are risky prospects with two possible realizations, and that one of these two realizations is fixed across the seven alternatives and the other varies across alternatives–i.e. it is not fixed.)

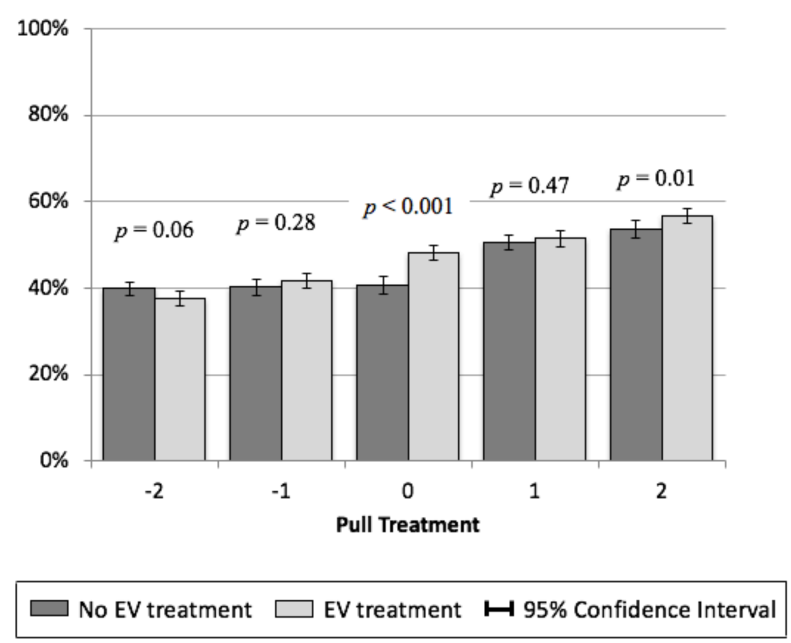
3 Summary Statistics of the Raw Data from the Experiment

Online Appendix Figures 3.1-3.4 show the percentage of choices where the safe option was chosen, by Pull and EV treatments, separately for Parts A, B, C, and D of the experiment. (For Part D, Online Appendix Figure 3.4 shows the percentage of choices where the option involving the smallest possible loss was selected.) The figures also show *p* values for *t*-tests of the equality of the percentages of safe choices across the two EV treatments within each Pull treatment. To compute the percentages, each row of the MPL was counted as a choice, and data from the 28 participants whose data were excluded from the estimation data for the main analyses in the main text (see Section 3.3 of the main text) were excluded here too. The figure captions provide additional details.

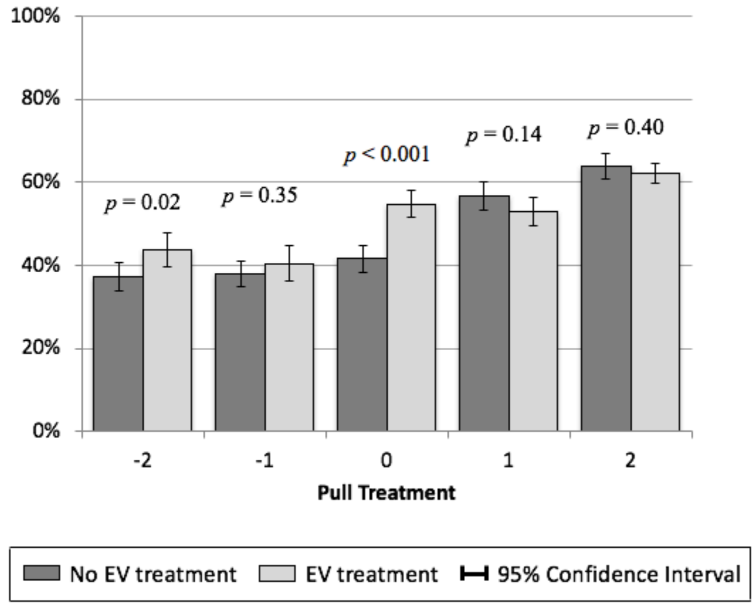
Although these figures may give readers a sense of the underlying data we collected in our experiment, caution is warranted when interpreting them because the different Pull treatments involve different sets of choices, and the raw data are thus not directly comparable across treatments. For example, consider Online Appendix Figure 3.1, which shows the percentages of safe choices in Part A. The percentages are lower in the Pull 2 treatment and higher in the Pull -2 treatment. Recall that the alternative prospects in the Pull 2 treatment involve amounts that are closer to zero, and the alternative prospects in the Pull -2 treatment involve amounts that are further away from zero. In the absence of a compromise effect, a participant with a given certainty equivalent for a gamble on a given screen will thus select the safe option less frequently in the Pull 2 treatment than in the Pull -2 treatment. The existence of a compromise effect would partially mitigate this tendency but would not fully counter it. Because of this, Online Appendix Figure 3.1 shows that the percentage of safe choices decreases in Pull, even though theoretical considerations suggest (see Section 4 of the main text), and our empirical results confirm, that estimates of risk aversion (i.e., $\hat{\gamma}$, $\hat{\gamma}^{+}$, $\hat{\gamma}^{-}$) increase in Pull.



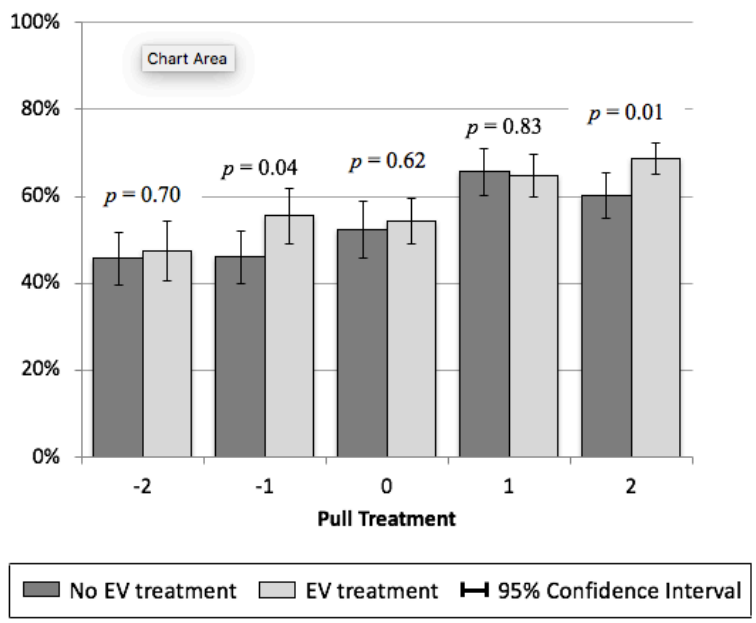
Online Appendix Figure 3.1. Percentage of choices where the safe option was chosen in Part A, by Pull and EV treatments. (In Part A, the safe options are the alternative prospects; each row of the MPL is counted as a choice.) The p values at the top of the bars are for t-tests of the equality of the percentages of safe choices across the two EV treatments within each Pull treatment.



Online Appendix Figure 3.2. Percentage of choices where the safe option was chosen in Part B, by Pull and EV treatments. (In Part B, the safe options are the alternative prospects; each row of the MPL is counted as a choice.) The p values at the top of the bars are for t-tests of the equality of the percentages of safe choices across the two EV treatments within each Pull treatment.



Online Appendix Figure 3.3. Percentage of choices where the safe option was chosen in Part C, by Pull and EV treatments. (In Part C, we define the safe option in a row as selecting "Don't take the gamble"; each row of the MPL is counted as a choice.) The *p* values at the top of the bars are for *t*-tests of the equality of the percentages of safe choices across the two EV treatments within each Pull treatment.



Online Appendix Figure 3.4. Percentage of choices where the option involving the smaller possible loss was chosen in Part D, by Pull and EV treatments. (All choices in Part D involve two gambles, gamble 1 and gamble 2, each of which involves a 50% chance of a loss; the possible loss in gamble 1 is always smaller than that in gamble 2; thus, the figure shows the percentage of choices where gamble 1 was selected; each row of the MPL is counted as a choice.) The *p* values at the top of the bars are for *t*-tests of the equality of the percentages of safe choices across the two EV treatments within each Pull treatment.

4 Complete Results for the Estimations Summarized in Tables 1-4 of the Paper

4.1 Complete Results for Table 1 in the Paper: ML Estimates of All Parameters in the Model with the Compromise Effect

4.1.1 Parts A-D Together

```
                                               Number of obs   =      30566
                                               Wald chi2(0)    =          .
Log pseudolikelihood = -55378.806              Prob > chi2     =          .

                           (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   .2417204   .0160087    15.10   0.000      .210344    .2730969
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .6193999   .0151086    41.00   0.000     .5897876    .6490122
-------------+----------------------------------------------------------------
beta         |
       _cons |   1.118809   .0245974    45.48   0.000     1.070599    1.167019
-------------+----------------------------------------------------------------
lambda       |
       _cons |   1.311381    .034214    38.33   0.000     1.244323    1.378439
-------------+----------------------------------------------------------------
sA1          |
       _cons |   6.946555   .3952036    17.58   0.000      6.17197    7.721139
-------------+----------------------------------------------------------------
sA2          |
       _cons |    11.9386   .7371196    16.20   0.000     10.49387    13.38333
-------------+----------------------------------------------------------------
sA3          |
       _cons |   14.78461   1.152642    12.83   0.000     12.52548    17.04375
-------------+----------------------------------------------------------------
sA4          |
       _cons |   24.60433   1.958008    12.57   0.000      20.7667    28.44196
-------------+----------------------------------------------------------------
sA5          |
       _cons |   50.82841   5.950401     8.54   0.000     39.16584    62.49098
-------------+----------------------------------------------------------------
sB1          |
       _cons |   12.75788   .8051541    15.85   0.000      11.1798    14.33595
-------------+----------------------------------------------------------------
sB2          |
       _cons |   18.61553   1.335685    13.94   0.000     15.99763    21.23342
-------------+----------------------------------------------------------------
sB3          |
       _cons |   19.94524   1.513185    13.18   0.000     16.97945    22.91103
-------------+----------------------------------------------------------------
sB4          |
       _cons |   26.32082   2.728525     9.65   0.000     20.97301    31.66864
-------------+----------------------------------------------------------------
sB5          |
       _cons |    38.0273   4.955181     7.67   0.000     28.31533    47.73928
-------------+----------------------------------------------------------------
sC1          |
       _cons |    7.88043   .5498168    14.33   0.000     6.802809    8.958052
-------------+----------------------------------------------------------------
sC2          |
       _cons |    19.3701   1.596884    12.13   0.000     16.24026    22.49993
-------------+----------------------------------------------------------------
sD           |
       _cons |   12.24018   1.141905    10.72   0.000     10.00209    14.47827
-------------+----------------------------------------------------------------
pi1          |
       _cons |  -.0907861   .0119494    -7.60   0.000    -.1142064   -.0673657
-------------+----------------------------------------------------------------
pi2          |
       _cons |  -.0075387     .00137    -5.50   0.000    -.0102238   -.0048537
------------------------------------------------------------------------------
```

4.1.2 Part A (Gain Domain Only)

```
                                           Number of obs    =      13804
                                                 Wald chi2(0)    =          .
Log pseudolikelihood = -23915.434                Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   .4475485   .0195434    22.90   0.000     .4092441    .4858529
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .5640233   .0146757    38.43   0.000     .5352594    .5927871
-------------+----------------------------------------------------------------
beta         |
       _cons |   .8581722   .0325624    26.35   0.000     .7943512    .9219933
-------------+----------------------------------------------------------------
sA1          |
       _cons |   3.884443   .1827219    21.26   0.000     3.526315    4.242572
-------------+----------------------------------------------------------------
sA2          |
       _cons |   5.745609    .326979    17.57   0.000     5.104742    6.386476
-------------+----------------------------------------------------------------
sA3          |
       _cons |   6.100672   .4205729    14.51   0.000     5.276364    6.924979
-------------+----------------------------------------------------------------
sA4          |
       _cons |   9.034794   .6918451    13.06   0.000     7.678803    10.39079
-------------+----------------------------------------------------------------
sA5          |
       _cons |   15.36957   1.827406     8.41   0.000     11.78792    18.95122
-------------+----------------------------------------------------------------
pi1          |
       _cons |  -.1344342   .0176732    -7.61   0.000    -.1690732   -.0997953
-------------+----------------------------------------------------------------
pi2          |
       _cons |   .0016748   .0019178     0.87   0.383    -.0020841    .0054337
------------------------------------------------------------------------------
```

4.1.3 Part B (Loss Domain Only)

```
                                                  Number of obs   =      13804
                                                  Wald chi2(0)    =          .
Log pseudolikelihood =  -25399.65                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |  -.1056974   .0431253    -2.45   0.014    -.1902214   -.0211734
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .6897954   .0220424    31.29   0.000     .6465931    .7329978
-------------+----------------------------------------------------------------
beta         |
       _cons |    1.47058   .0611999    24.03   0.000      1.35063    1.590529
-------------+----------------------------------------------------------------
sB1          |
       _cons |   26.54978   3.935111     6.75   0.000     18.83711    34.26246
-------------+----------------------------------------------------------------
sB2          |
       _cons |   48.94547   8.469511     5.78   0.000     32.34554    65.54541
-------------+----------------------------------------------------------------
sB3          |
       _cons |   66.25618   13.01421     5.09   0.000     40.74879    91.76357
-------------+----------------------------------------------------------------
sB4          |
       _cons |   107.4424   23.30718     4.61   0.000      61.7612    153.1237
-------------+----------------------------------------------------------------
sB5          |
       _cons |   217.0596   56.99872     3.81   0.000     105.3442    328.7751
-------------+----------------------------------------------------------------
pi1          |
       _cons |   -.144331    .018166    -7.95   0.000    -.1799357   -.1087262
-------------+----------------------------------------------------------------
pi2          |
       _cons |  -.0043143   .0022595    -1.91   0.056    -.0087428    .0001143
------------------------------------------------------------------------------
```

4.2 Complete Results for Table 2 in the Paper: ML Estimates of All Parameters in the Parameterized Model with the Compromise Effect

4.2.1 Parts A-D Together

```
                                                  Number of obs   =      30566
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -55224.557                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gamma						
_cons	.206111	.0256492	8.04	0.000	.1558395	.2563824
alpha						
_cons	.5557754	.0185143	30.02	0.000	.5194881	.5920627
beta						
_cons	1.189692	.037368	31.84	0.000	1.116453	1.262932
lambda						
_cons	1.270673	.0533319	23.83	0.000	1.166145	1.375202
phi1_gamma						
_cons	.0083344	.0172273	0.48	0.629	-.0254305	.0420994
phi2_gamma						
_cons	.0576824	.0350184	1.65	0.100	-.0109523	.1263172
phi1_alpha						
_cons	-.0174391	.0092667	-1.88	0.060	-.0356014	.0007233
phi2_alpha						
_cons	.1302331	.0284477	4.58	0.000	.0744766	.1859896
phi1_beta						
_cons	-.0004308	.0219806	-0.02	0.984	-.0435121	.0426504
phi2_beta						
_cons	-.1321397	.0476646	-2.77	0.006	-.2255607	-.0387187
phi1_l						
_cons	-.0531334	.0293479	-1.81	0.070	-.1106541	.0043874
phi2_l						
_cons	.0749102	.0741481	1.01	0.312	-.0704173	.2202377
sA1						
_cons	8.471337	.7346861	11.53	0.000	7.031379	9.911295
sA2						
_cons	13.99402	1.328479	10.53	0.000	11.39024	16.59779
sA3						
_cons	15.8456	1.954131	8.11	0.000	12.01557	19.67562
sA4						
_cons	29.64206	3.712833	7.98	0.000	22.36504	36.91908
sA5						
_cons	66.62124	11.41515	5.84	0.000	44.24796	88.99452
sB1						
_cons	14.62046	1.472035	9.93	0.000	11.73532	17.50559
sB2						
_cons	21.02752	2.417808	8.70	0.000	16.2887	25.76634
sB3						
_cons	24.01024	3.085625	7.78	0.000	17.96252	30.05795
sB4						
_cons	29.3427	4.5028	6.52	0.000	20.51737	38.16802

sB5						
_cons	46.349	8.681106	5.34	0.000	29.33435	63.36366
sC1						
_cons	8.091364	.9009637	8.98	0.000	6.325508	9.85722
sC2						
_cons	20.51948	2.878159	7.13	0.000	14.8784	26.16057
sD						
_cons	16.03147	2.278884	7.03	0.000	11.56494	20.49801
phi1_sA1						
_cons	.0787081	.3413576	0.23	0.818	-.5903405	.7477566
phi2_sA1						
_cons	-2.757494	.8594604	-3.21	0.001	-4.442005	-1.072982
phi1_sA2						
_cons	.0824369	.7700597	0.11	0.915	-1.426852	1.591726
phi2_sA2						
_cons	-3.545769	1.657203	-2.14	0.032	-6.793827	-.2977101
phi1_sA3						
_cons	.2790316	1.095298	0.25	0.799	-1.867712	2.425776
phi2_sA3						
_cons	-1.995147	2.573782	-0.78	0.438	-7.039667	3.049372
phi1_sA4						
_cons	-3.35317	2.193181	-1.53	0.126	-7.651726	.9453867
phi2_sA4						
_cons	-6.249444	4.151368	-1.51	0.132	-14.38598	1.887088
phi1_sA5						
_cons	-6.356309	6.008805	-1.06	0.290	-18.13335	5.420733
phi2_sA5						
_cons	-21.68732	12.76104	-1.70	0.089	-46.69849	3.323855
phi1_sB1						
_cons	-.3858308	.747751	-0.52	0.606	-1.851396	1.079734
phi2_sB1						
_cons	-3.229005	1.798479	-1.80	0.073	-6.75396	.2959493
phi1_sB2						
_cons	-.8176172	1.426382	-0.57	0.567	-3.613275	1.978041
phi2_sB2						
_cons	-4.1457	2.926864	-1.42	0.157	-9.882248	1.590848
phi1_sB3						
_cons	-1.020451	1.586598	-0.64	0.520	-4.130126	2.089223
phi2_sB3						
_cons	-6.994841	3.584155	-1.95	0.051	-14.01966	.0299745
phi1_sB4						
_cons	-2.661792	2.884826	-0.92	0.356	-8.315947	2.992364
phi2_sB4						
_cons	-4.413494	5.222461	-0.85	0.398	-14.64933	5.822341
phi1_sB5						
_cons	-8.1278	4.800149	-1.69	0.090	-17.53592	1.28032
phi2_sB5						
_cons	-7.753461	9.176378	-0.84	0.398	-25.73883	10.23191
phi1_sC1						
_cons	-.5049022	.4824912	-1.05	0.295	-1.450567	.4407631
phi2_sC1						
_cons	-.21316	1.213742	-0.18	0.861	-2.592051	2.165731
phi1_sC2						
_cons	-1.76451	1.556722	-1.13	0.257	-4.81563	1.286609

```
-------------+----------------------------------------------------------------
phi2_sC2     |
       _cons |  -1.913247   3.618202    -0.53   0.597    -9.004794    5.178299
-------------+----------------------------------------------------------------
phi1_sD      |
       _cons |  -1.814308   1.001584    -1.81   0.070    -3.777376      .14876
-------------+----------------------------------------------------------------
phi2_sD      |
       _cons |  -5.404312   2.380116    -2.27   0.023    -10.06925   -.7393695
-------------+----------------------------------------------------------------
pi1          |
       _cons |  -.0896071   .0122324    -7.33   0.000    -.1135822    -.065632
-------------+----------------------------------------------------------------
pi2          |
       _cons |  -.0076155   .0013797    -5.52   0.000    -.0103198   -.0049113
------------------------------------------------------------------------------
```

4.2.2 Part A (Gain Domain Only)

```
                                                  Number of obs   =      13804
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -23838.856                 Prob > chi2     =          .

                           (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   .4234537   .0278263    15.22   0.000     .3689151    .4779922
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .5051478   .0183603    27.51   0.000     .4691622    .5411334
-------------+----------------------------------------------------------------
beta         |
       _cons |   .9105968   .0478594    19.03   0.000     .8167942    1.004399
-------------+----------------------------------------------------------------
phi1_gamma   |
       _cons |   .0110312   .0178499     0.62   0.537    -.0239539    .0460163
-------------+----------------------------------------------------------------
phi2_gamma   |
       _cons |   .0334443   .0391302     0.85   0.393    -.0432496    .1101381
-------------+----------------------------------------------------------------
phi1_alpha   |
       _cons |  -.0150514   .0090778    -1.66   0.097    -.0328434    .0027407
-------------+----------------------------------------------------------------
phi2_alpha   |
       _cons |   .1242067   .0276327     4.49   0.000     .0700477    .1783657
-------------+----------------------------------------------------------------
phi1_beta    |
       _cons |   -.004172   .0267502    -0.16   0.876    -.0566015    .0482574
-------------+----------------------------------------------------------------
phi2_beta    |
       _cons |   -.095354   .0633599    -1.50   0.132    -.2195372    .0288292
-------------+----------------------------------------------------------------
sA1          |
       _cons |   4.496528   .2830979    15.88   0.000     3.941666     5.05139
-------------+----------------------------------------------------------------
sA2          |
       _cons |   6.404707   .4869965    13.15   0.000     5.450211    7.359202
-------------+----------------------------------------------------------------
sA3          |
       _cons |   6.242768   .5770657    10.82   0.000      5.11174    7.373796
-------------+----------------------------------------------------------------
sA4          |
       _cons |   10.20512    1.10953     9.20   0.000      8.03048    12.37976
-------------+----------------------------------------------------------------
sA5          |
       _cons |   18.74995   3.110022     6.03   0.000     12.65442    24.84548
-------------+----------------------------------------------------------------
phi1_sA1     |
       _cons |   .0212634   .1603163     0.13   0.894    -.2929508    .3354776
-------------+----------------------------------------------------------------
phi2_sA1     |
       _cons |  -1.149381   .3552096    -3.24   0.001    -1.845579   -.4531833
-------------+----------------------------------------------------------------
phi1_sA2     |
       _cons |   .0265432    .318068     0.08   0.933    -.5968587    .6499451
-------------+----------------------------------------------------------------
phi2_sA2     |
       _cons |  -1.144326   .6541053    -1.75   0.080    -2.426349    .1376964
-------------+----------------------------------------------------------------
phi1_sA3     |
       _cons |   .2628053   .3820786     0.69   0.492     -.486055    1.011665
-------------+----------------------------------------------------------------
phi2_sA3     |
       _cons |  -.3724247   .8463344    -0.44   0.660     -2.03121     1.28636
-------------+----------------------------------------------------------------
phi1_sA4     |
       _cons |  -.9776202   .7639582    -1.28   0.201    -2.474951    .5197105
-------------+----------------------------------------------------------------
phi2_sA4     |
       _cons |  -1.321611   1.373165    -0.96   0.336    -4.012966    1.369743
-------------+----------------------------------------------------------------
phi1_sA5     |
       _cons |  -1.934792   1.857262    -1.04   0.298    -5.574958    1.705374
```

```
-------------+----------------------------------------------------------------
phi2_sA5     |
       _cons |  -4.312429   3.602988    -1.20   0.231    -11.37416    2.749297
-------------+----------------------------------------------------------------
pi1          |
       _cons |  -.1387867   .0178033    -7.80   0.000    -.1736807   -.1038928
-------------+----------------------------------------------------------------
pi2          |
       _cons |   .0023069   .0018789     1.23   0.220    -.0013756    .0059895
------------------------------------------------------------------------------
```

4.2.3 Part B (Loss Domain Only)

```
                                                  Number of obs   =      13804
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -25343.262                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |  -.1182055   .0515039    -2.30   0.022    -.2191512   -.0172598
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .6167516   .0270155    22.83   0.000     .5638022    .6697009
-------------+----------------------------------------------------------------
beta         |
       _cons |   1.524137   .0864916    17.62   0.000     1.354616    1.693657
-------------+----------------------------------------------------------------
phi1_gamma   |
       _cons |  -.0323206    .026049    -1.24   0.215    -.0833758    .0187345
-------------+----------------------------------------------------------------
phi2_gamma   |
       _cons |   .0021699   .0666094     0.03   0.974    -.1283821    .1327218
-------------+----------------------------------------------------------------
phi1_alpha   |
       _cons |   -.015365   .0138902    -1.11   0.269    -.0425892    .0118593
-------------+----------------------------------------------------------------
phi2_alpha   |
       _cons |   .1562935    .041995     3.72   0.000     .0739848    .2386022
-------------+----------------------------------------------------------------
phi1_beta    |
       _cons |   .0416922   .0419585     0.99   0.320     -.040545    .1239294
-------------+----------------------------------------------------------------
phi2_beta    |
       _cons |  -.0899068   .1142436    -0.79   0.431    -.3138202    .1340066
-------------+----------------------------------------------------------------
sB1          |
       _cons |   30.30175   5.372766     5.64   0.000     19.77132    40.83218
-------------+----------------------------------------------------------------
sB2          |
       _cons |   54.05663   11.22242     4.82   0.000     32.06108    76.05217
-------------+----------------------------------------------------------------
sB3          |
       _cons |   77.57128   18.36838     4.22   0.000     41.56992    113.5726
-------------+----------------------------------------------------------------
sB4          |
       _cons |   114.6108    29.8461     3.84   0.000     56.11348     173.108
-------------+----------------------------------------------------------------
sB5          |
       _cons |   245.3845   78.64632     3.12   0.002      91.2406    399.5285
-------------+----------------------------------------------------------------
phi1_sB1     |
       _cons |    3.35427   2.574001     1.30   0.193     -1.69068    8.399219
-------------+----------------------------------------------------------------
phi2_sB1     |
       _cons |  -4.428698   6.519832    -0.68   0.497    -17.20733    8.349938
-------------+----------------------------------------------------------------
phi1_sB2     |
       _cons |   8.864135   6.508522     1.36   0.173    -3.892334     21.6206
-------------+----------------------------------------------------------------
phi2_sB2     |
       _cons |   -2.77284   13.97422    -0.20   0.843    -30.16182    24.61614
-------------+----------------------------------------------------------------
phi1_sB3     |
       _cons |   10.54686   9.041151     1.17   0.243    -7.173474    28.26719
-------------+----------------------------------------------------------------
phi2_sB3     |
       _cons |  -12.92712   20.86169    -0.62   0.535    -53.81528    27.96105
-------------+----------------------------------------------------------------
phi1_sB4     |
       _cons |   16.18807   17.86578     0.91   0.365    -18.82821    51.20435
-------------+----------------------------------------------------------------
phi2_sB4     |
       _cons |   1.286831   41.29134     0.03   0.975    -79.64271    82.21637
-------------+----------------------------------------------------------------
phi1_sB5     |
       _cons |    13.1091   39.94809     0.33   0.743    -65.18772    91.40592
-------------+----------------------------------------------------------------
phi2_sB5     |
       _cons |  -5.218528   102.6074    -0.05   0.959    -206.3253    195.8882
```

```
-------------+----------------------------------------------------------------
pi1          |
       _cons |  -.1416346   .0175073    -8.09   0.000    -.1759483    -.107321
-------------+----------------------------------------------------------------
pi2          |
       _cons |  -.0048271   .0022178    -2.18   0.030    -.0091739   -.0004803
------------------------------------------------------------------------------
```

4.3 Complete Results for Table 3 in the Paper: ML Estimates of All Parameters in the Model Without the Compromise Effect

4.3.1 Parts A-D Together

```
   Number of obs   =      30566
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -59956.628                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   .2032792   .0118117    17.21   0.000     .1801287    .2264296
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .5742118   .0099229    57.87   0.000     .5547632    .5936604
-------------+----------------------------------------------------------------
beta         |
       _cons |   1.123419    .016066    69.93   0.000      1.09193    1.154908
-------------+----------------------------------------------------------------
lambda       |
       _cons |   1.336537    .027142    49.24   0.000     1.283339    1.389734
-------------+----------------------------------------------------------------
sA1          |
       _cons |   5.708549    .239734    23.81   0.000     5.238679    6.178419
-------------+----------------------------------------------------------------
sA2          |
       _cons |    9.63376   .4560246    21.13   0.000     8.739968    10.52755
-------------+----------------------------------------------------------------
sA3          |
       _cons |   10.28831   .6149238    16.73   0.000     9.083077    11.49353
-------------+----------------------------------------------------------------
sA4          |
       _cons |   16.67114   1.062706    15.69   0.000     14.58827      18.754
-------------+----------------------------------------------------------------
sA5          |
       _cons |   40.83873   3.415513    11.96   0.000     34.14445    47.53302
-------------+----------------------------------------------------------------
sB1          |
       _cons |   9.962969   .5151478    19.34   0.000     8.953298    10.97264
-------------+----------------------------------------------------------------
sB2          |
       _cons |    14.3498   .8522449    16.84   0.000     12.67943    16.02017
-------------+----------------------------------------------------------------
sB3          |
       _cons |   13.56155   .8975655    15.11   0.000     11.80235    15.32075
-------------+----------------------------------------------------------------
sB4          |
       _cons |   18.37978   1.542214    11.92   0.000     15.35709    21.40246
-------------+----------------------------------------------------------------
sB5          |
       _cons |   35.11393   3.572159     9.83   0.000     28.11263    42.11524
-------------+----------------------------------------------------------------
sC1          |
       _cons |   6.672262   .3618274    18.44   0.000     5.963093    7.381431
-------------+----------------------------------------------------------------
sC2          |
       _cons |   17.22871   1.122964    15.34   0.000     15.02774    19.42968
-------------+----------------------------------------------------------------
sD           |
       _cons |   9.602215   .6499856    14.77   0.000     8.328267    10.87616
------------------------------------------------------------------------------
```

4.3.2 Part A (Gain Domain Only)

```
                                                Number of obs   =      13804
                                                Wald chi2(0)    =          .
Log pseudolikelihood = -25604.111               Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   .3626102   .0138369    26.21   0.000     .3354904      .38973
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .5384385   .0109185    49.31   0.000     .5170386    .5598384
-------------+----------------------------------------------------------------
beta         |
       _cons |   .9583001   .0197127    48.61   0.000     .9196639    .9969363
-------------+----------------------------------------------------------------
sA1          |
       _cons |   3.818816   .1399444    27.29   0.000      3.54453    4.093102
-------------+----------------------------------------------------------------
sA2          |
       _cons |   5.622384   .2526493    22.25   0.000       5.1272    6.117567
-------------+----------------------------------------------------------------
sA3          |
       _cons |   5.233887   .3046054    17.18   0.000     4.636871    5.830902
-------------+----------------------------------------------------------------
sA4          |
       _cons |   7.676197   .4847189    15.84   0.000     6.726165    8.626228
-------------+----------------------------------------------------------------
sA5          |
       _cons |   16.47294   1.412336    11.66   0.000     13.70481    19.24107
------------------------------------------------------------------------------
```

4.3.3 Part B (Loss Domain Only)

```
                                                Number of obs   =      13804
                                                   Wald chi2(0)    =          .
Log pseudolikelihood = -28140.868                  Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |   -.009619    .021813    -0.44   0.659    -.0523716    .0331337
-------------+----------------------------------------------------------------
alpha        |
       _cons |   .6153074   .0130953    46.99   0.000      .589641    .6409737
-------------+----------------------------------------------------------------
beta         |
       _cons |   1.296382   .0301646    42.98   0.000      1.23726    1.355503
-------------+----------------------------------------------------------------
sB1          |
       _cons |   12.89018    .973089    13.25   0.000     10.98297     14.7974
-------------+----------------------------------------------------------------
sB2          |
       _cons |   22.02498   1.999303    11.02   0.000     18.10642    25.94354
-------------+----------------------------------------------------------------
sB3          |
       _cons |    24.2498   2.615078     9.27   0.000     19.12434    29.37526
-------------+----------------------------------------------------------------
sB4          |
       _cons |   38.28514   4.688734     8.17   0.000     29.09539    47.47489
-------------+----------------------------------------------------------------
sB5          |
       _cons |   90.63866   13.18273     6.88   0.000     64.80098    116.4763
------------------------------------------------------------------------------
```

4.4 Complete Results for Table 4 in the Paper: ML Estimates of All Parameters in the Parameterized Model Without the Compromise Effect

4.4.1 Parts A-D Together

```
Number of obs    =      30566
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -59426.702                 Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gamma						
_cons	.1962763	.0159212	12.33	0.000	.1650714	.2274813
alpha						
_cons	.5353259	.0123991	43.17	0.000	.5110242	.5596277
beta						
_cons	1.143144	.0219723	52.03	0.000	1.100079	1.186209
lambda						
_cons	1.317612	.0396838	33.20	0.000	1.239834	1.395391
phi1_gamma						
_cons	.0415339	.0089828	4.62	0.000	.023928	.0591398
phi2_gamma						
_cons	.0008474	.0233336	0.04	0.971	-.0448856	.0465805
phi1_alpha						
_cons	-.0352166	.0062937	-5.60	0.000	-.0475521	-.0228811
phi2_alpha						
_cons	.0886372	.0185971	4.77	0.000	.0521876	.1250869
phi1_beta						
_cons	.02773	.0100495	2.76	0.006	.0080333	.0474268
phi2_beta						
_cons	-.0405865	.0276623	-1.47	0.142	-.0948035	.0136306
phi1_l						
_cons	-.1465308	.0217653	-6.73	0.000	-.1891899	-.1038716
phi2_l						
_cons	.0856586	.058742	1.46	0.145	-.0294736	.2007907
sA1						
_cons	6.202134	.3622788	17.12	0.000	5.492081	6.912187
sA2						
_cons	10.20917	.6587717	15.50	0.000	8.918006	11.50034
sA3						
_cons	10.37908	.8519371	12.18	0.000	8.709315	12.04885
sA4						
_cons	18.00332	1.480613	12.16	0.000	15.10137	20.90527
sA5						
_cons	44.42177	4.854223	9.15	0.000	34.90767	53.93588
sB1						
_cons	10.66456	.7235959	14.74	0.000	9.246338	12.08278
sB2						
_cons	15.45323	1.193821	12.94	0.000	13.11338	17.79307
sB3						
_cons	14.8943	1.267181	11.75	0.000	12.41067	17.37793

sB4						
_cons	19.47978	2.045269	9.52	0.000	15.47113	23.48844
sB5						
_cons	39.81084	4.923973	8.09	0.000	30.16004	49.46165
sC1						
_cons	6.942697	.5228935	13.28	0.000	5.917845	7.967549
sC2						
_cons	18.2909	1.636653	11.18	0.000	15.08312	21.49868
sD						
_cons	11.0663	.9256105	11.96	0.000	9.252138	12.88046
phi1_sA1						
_cons	-.3837757	.165735	-2.32	0.021	-.7086103	-.0589412
phi2_sA1						
_cons	-1.023599	.4515057	-2.27	0.023	-1.908534	-.1386645
phi1_sA2						
_cons	-1.05196	.3478069	-3.02	0.002	-1.733649	-.3702714
phi2_sA2						
_cons	-.8517713	.882325	-0.97	0.334	-2.581096	.8775539
phi1_sA3						
_cons	-1.162615	.4383028	-2.65	0.008	-2.021672	-.303557
phi2_sA3						
_cons	-.1026005	1.145723	-0.09	0.929	-2.348177	2.142976
phi1_sA4						
_cons	-3.27874	.8584398	-3.82	0.000	-4.961251	-1.596229
phi2_sA4						
_cons	-.6770411	1.895494	-0.36	0.721	-4.392141	3.038059
phi1_sA5						
_cons	-8.270104	2.730715	-3.03	0.002	-13.62221	-2.918001
phi2_sA5						
_cons	-2.279285	5.984907	-0.38	0.703	-14.00949	9.450918
phi1_sB1						
_cons	-1.921642	.3686271	-5.21	0.000	-2.644137	-1.199146
phi2_sB1						
_cons	-.4233126	.8821363	-0.48	0.631	-2.152268	1.305643
phi1_sB2						
_cons	-3.230316	.6095607	-5.30	0.000	-4.425033	-2.035599
phi2_sB2						
_cons	-.4855926	1.32408	-0.37	0.714	-3.080741	2.109556
phi1_sB3						
_cons	-3.529583	.6733545	-5.24	0.000	-4.849334	-2.209832
phi2_sB3						
_cons	-.7983987	1.497648	-0.53	0.594	-3.733734	2.136937
phi1_sB4						
_cons	-5.021189	1.159367	-4.33	0.000	-7.293506	-2.748872
phi2_sB4						
_cons	.6409199	2.176438	0.29	0.768	-3.624821	4.906661
phi1_sB5						
_cons	-12.37504	2.595848	-4.77	0.000	-17.46281	-7.287273
phi2_sB5						
_cons	1.847428	4.616137	0.40	0.689	-7.200034	10.89489
phi1_sC1						
_cons	-1.409292	.2647771	-5.32	0.000	-1.928246	-.8903385
phi2_sC1						
_cons	.1640563	.6275231	0.26	0.794	-1.065866	1.393979

phi1_sC2						
_cons	-4.479169	.8319998	-5.38	0.000	-6.109859	-2.848479
phi2_sC2						
_cons	.2207494	1.770406	0.12	0.901	-3.249184	3.690682
phi1_sD						
_cons	-2.736951	.5005148	-5.47	0.000	-3.717942	-1.75596
phi2_sD						
_cons	-.8269326	1.058469	-0.78	0.435	-2.901493	1.247628

4.4.2 Part A (Gain Domain Only)

```
                                                  Number of obs   =      13804
                                                   Wald chi2(0)    =          .
Log pseudolikelihood = -25405.825                  Prob > chi2     =          .

                            (Std. Err. adjusted for 493 clusters in subjectId)
------------------------------------------------------------------------------
             |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gamma        |
       _cons |    .353284   .0182659    19.34   0.000     .3174835    .3890845
-------------+----------------------------------------------------------------
alpha       |
       _cons |    .497086   .0139917    35.53   0.000     .4696627    .5245093
-------------+----------------------------------------------------------------
beta        |
       _cons |   .9801244    .027654    35.44   0.000     .9259235    1.034325
-------------+----------------------------------------------------------------
phi1_gamma      |
       _cons |   .0405741   .0120417     3.37   0.001     .0169728    .0641755
-------------+----------------------------------------------------------------
phi2_gamma      |
       _cons |   .0025484    .028743     0.09   0.929    -.0537868    .0588837
-------------+----------------------------------------------------------------
phi1_alpha     |
       _cons |  -.0305431   .0070018    -4.36   0.000    -.0442663   -.0168198
-------------+----------------------------------------------------------------
phi2_alpha     |
       _cons |   .0930661   .0210508     4.42   0.000     .0518073    .1343249
-------------+----------------------------------------------------------------
phi1_beta     |
       _cons |   .0053596   .0154684     0.35   0.729    -.0249578    .0356771
-------------+----------------------------------------------------------------
phi2_beta     |
       _cons |  -.0445406    .038949    -1.14   0.253    -.1208792    .0317981
-------------+----------------------------------------------------------------
sA1          |
       _cons |   4.148472   .2173676    19.09   0.000     3.722439    4.574505
-------------+----------------------------------------------------------------
sA2          |
       _cons |   5.968931   .3746306    15.93   0.000     5.234669    6.703194
-------------+----------------------------------------------------------------
sA3          |
       _cons |   5.309521    .433876    12.24   0.000     4.459139    6.159902
-------------+----------------------------------------------------------------
sA4          |
       _cons |   8.322197   .7192379    11.57   0.000     6.912516    9.731877
-------------+----------------------------------------------------------------
sA5          |
       _cons |   18.08268   2.036236     8.88   0.000     14.09173    22.07363
-------------+----------------------------------------------------------------
phi1_sA1    |
       _cons |  -.2270423   .1240069    -1.83   0.067    -.4700913    .0160067
-------------+----------------------------------------------------------------
phi2_sA1    |
       _cons |  -.6813952   .3070209    -2.22   0.026    -1.283145   -.0796452
-------------+----------------------------------------------------------------
phi1_sA2    |
       _cons |  -.5242444    .238329    -2.20   0.028    -.9913607   -.0571282
-------------+----------------------------------------------------------------
phi2_sA2    |
       _cons |  -.5413533   .5415599    -1.00   0.317    -1.602791    .5200845
-------------+----------------------------------------------------------------
phi1_sA3    |
       _cons |  -.5326923   .2629498    -2.03   0.043    -1.048064   -.0173202
-------------+----------------------------------------------------------------
phi2_sA3    |
       _cons |  -.1230266   .6450056    -0.19   0.849    -1.387214    1.141161
-------------+----------------------------------------------------------------
phi1_sA4    |
       _cons |  -1.405904   .4909182    -2.86   0.004    -2.368086   -.4437217
-------------+----------------------------------------------------------------
phi2_sA4    |
       _cons |  -.3779393   .9823201    -0.38   0.700    -2.303251    1.547373
-------------+----------------------------------------------------------------
phi1_sA5    |
       _cons |  -3.254219   1.354181    -2.40   0.016    -5.908365   -.6000737
-------------+----------------------------------------------------------------
phi2_sA5    |
       _cons |  -1.032615   2.713097    -0.38   0.703    -6.350188    4.284959
------------------------------------------------------------------------------
```

4.4.3 Part B (Loss Domain Only)

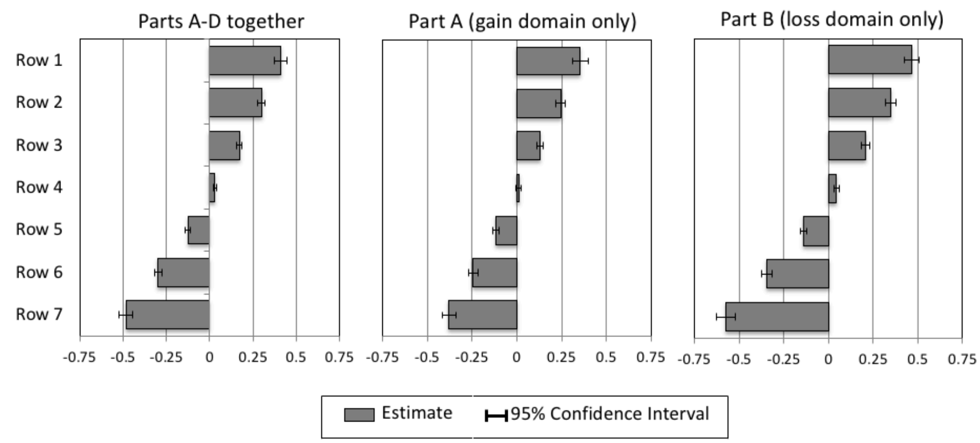
```
                                                  Number of obs   =      13804
                                                  Wald chi2(0)    =          .
Log pseudolikelihood = -27851.955                 Prob > chi2     =          .

                           (Std. Err. adjusted for 493 clusters in subjectId)
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gamma _cons	-.0031566	.0260451	-0.12	0.904	-.0542041	.0478909
alpha _cons	.5772309	.016438	35.12	0.000	.545013	.6094489
beta _cons	1.30456	.0371034	35.16	0.000	1.231839	1.377282
phi1_gamma _cons	.063236	.0116521	5.43	0.000	.0403983	.0860737
phi2_gamma _cons	-.0219581	.0303238	-0.72	0.469	-.0813916	.0374754
phi1_alpha _cons	-.0425013	.0082642	-5.14	0.000	-.0586988	-.0263039
phi2_alpha _cons	.0889148	.0248289	3.58	0.000	.040251	.1375785
phi1_beta _cons	.0392595	.0147204	2.67	0.008	.010408	.068111
phi2_beta _cons	-.0233409	.0398406	-0.59	0.558	-.1014271	.0547452
sB1 _cons	13.53282	1.195238	11.32	0.000	11.19019	15.87544
sB2 _cons	22.99171	2.437006	9.43	0.000	18.21527	27.76816
sB3 _cons	25.49915	3.128879	8.15	0.000	19.36666	31.63164
sB4 _cons	39.57846	5.502788	7.19	0.000	28.79319	50.36372
sB5 _cons	100.1441	16.38849	6.11	0.000	68.02324	132.2649
phi1_sB1 _cons	-2.036972	.4820761	-4.23	0.000	-2.981824	-1.09212
phi2_sB1 _cons	-.5454671	1.147932	-0.48	0.635	-2.795372	1.704438
phi1_sB2 _cons	-4.321136	.9942535	-4.35	0.000	-6.269837	-2.372435
phi2_sB2 _cons	-.3476178	2.106143	-0.17	0.869	-4.475582	3.780347
phi1_sB3 _cons	-5.536534	1.292043	-4.29	0.000	-8.068892	-3.004175
phi2_sB3 _cons	-.7679326	2.732935	-0.28	0.779	-6.124387	4.588522
phi1_sB4 _cons	-10.11871	2.497848	-4.05	0.000	-15.0144	-5.223022
phi2_sB4 _cons	2.072809	4.528289	0.46	0.647	-6.802474	10.94809
phi1_sB5 _cons	-32.18525	7.360669	-4.37	0.000	-46.6119	-17.7586
phi2_sB5 _cons	7.573371	11.6346	0.65	0.515	-15.23002	30.37677

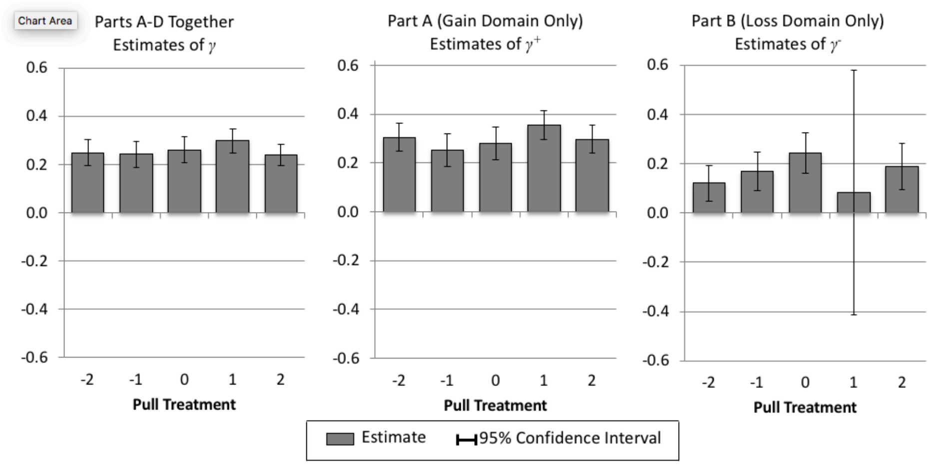
5 Results of Robustness Check with CPT Model with T&K's Probability Weighting Function

As a robustness check, we estimated the CPT model with T&K's probability weighting function ($\omega(p) = p^{\alpha}/(p^{\alpha} + (1-p)^{\alpha})^{1/\alpha}$) instead of the Prelec (1998) probability weighting function. As in the baseline model, utility $u(\cdot)$ is assumed to take the CRRA form (a.k.a. "power utility"), $u(\cdot) = \frac{x^{1-\gamma}}{1-\gamma}$.

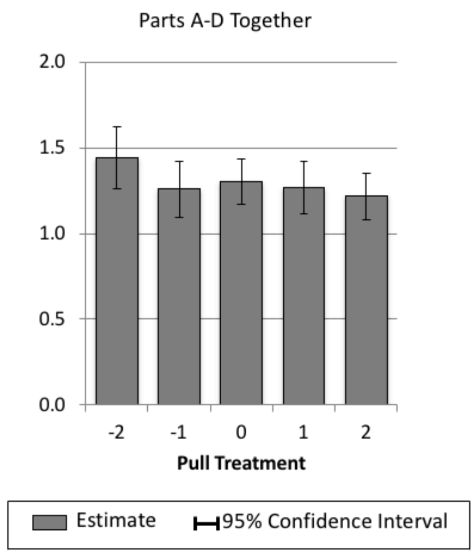
Online Appendix Figures 7.1-7.5 and Online Appendix Tables 7.1-7.4 below are analogous to Figures 2-6 and Tables 1-4 in the main text, respectively, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.



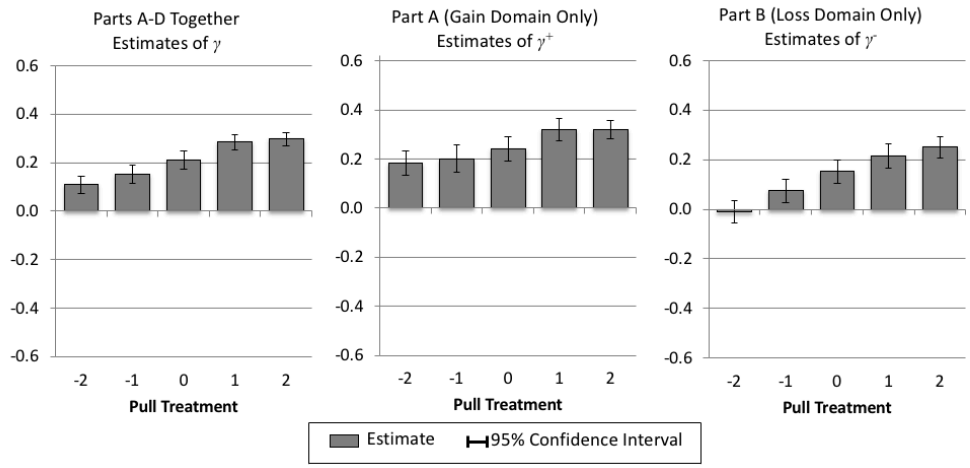
Online Appendix Figure 5.1. Implied estimates of the parameters for the compromise effect c_i as a function of the row i in which a choice appears. This figure is analogous to Figure 2 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.



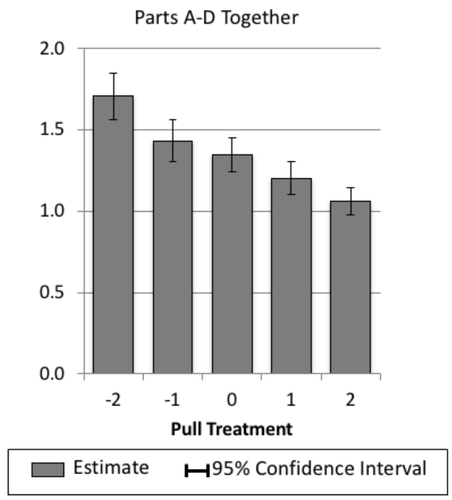
Online Appendix Figure 5.2. Estimates of γ, γ^+ and γ^- by Pull treatment, from the model with the compromise effect. This figure is analogous to Figure 3 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.



Online Appendix Figure 5.3. Estimates of λ by Pull treatment from the model with the compromise effect, for Parts A-D together. This figure is analogous to Figure 4 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.



Online Appendix Figure 5.4. Estimates of γ, γ^+ and γ^- by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 5 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.



Online Appendix Figure 5.5. Estimates of λ by Pull treatment from the model without the compromise effect, for Parts A-D together. This figure is analogous to Figure 6 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.

Online Appendix Table 5.1. ML Estimates of Selected Parameters in the Model with the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma, \gamma^+, \gamma^-$	0.267***	0.298***	0.202***
	(0. 011)	(0. 014)	(0. 018)
λ	1.292***		
	(0.034)		
$\alpha, \alpha^+, \alpha^-$	0.645***	0.617***	0.689***
	(0.011)	(0.011)	(0.019)
π_1	-0.089***	-0.102***	-0.084***
	(0.012)	(0.017)	(.017)
π_2	-0.008***	-0. 003	-0.011***
	(0.001)	(0.002)	(0.002)
Log-likelihood	-55,357	-24,018	-25,537
Wald test for π_1, π_2	$p < 1\times10^{-144}$	$p < 1\times10^{-80}$	$p < 1\times10^{-122}$
Parameters	18	9	9
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 1 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 5.2. ML Estimates of Selected Parameters in the Parameterized Model with the Compromise Effect

		Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma, \gamma^+, \gamma^-$	γ_0	0.247***	0.283***	0.185***
		(0.018)	(0.021)	(0.025)
	ϕ_1^γ	0.003	0.004	0.006
		(0.009)	(0.010)	(0.014)
	ϕ_2^γ	0.027	.0196	0.018
		(0.024)	(0.028)	(0.034)
λ	λ_0	1.24***		
		(0.049)		
	ϕ_1^λ	-0.048*		
		(0.025)		
	ϕ_2^λ	0.094		
		(0.069)		
$\alpha, \alpha^+, \alpha^-$		0.597***	0.577***	0.630***
		(0.014)	(.014)	(0.021)
π_1		-0.088***	-0.105***	-0.078***
		(0.012)	(0.017)	(0.017)
π_2		-0.008***	-0.002	-0.012***
		(0.001)	(0.002)	(0.002)
Log-likelihood		-55,203	-23,942	-25,476
Wald test for π_1, π_2		$p < 1\times10^{-134}$	$p < 1\times10^{-84}$	$p < 1\times10^{-112}$
Parameters		50	23	23
Individuals		493	493	493
Observations		30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 2 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 5.3. ML Estimates of Selected Parameters in the Model Without the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma, \gamma^+, \gamma^-$	0.219***	0.260***	0.144***
	(0.008)	(0.011)	(0.012)
λ	1.32***		
	(0.027)		
$\alpha, \alpha^+, \alpha^-$	0.615***	0.599***	0.631***
	(0.007)	(0.008)	(0.010)
Log-likelihood	-59,862	-25,681	-28,223
Parameters	16	7	7
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 3 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 5.4. ML Estimates of Selected Parameters in the Parameterized Model Without the Compromise Effect

		Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma, \gamma^+, \gamma^-$	γ_0	0.206***	0.247***	0.137***
		(0.012)	(0.015)	(0.017)
	ϕ_1^γ	0.044***	0.041***	0.061***
		(0.006)	(0.007)	(0.009)
	ϕ_2^γ	0.009	0.010	-0.003
		(0.018)	(0.021)	(0.025)
λ	λ_0	1.31***		
		(0.040)		
	ϕ_1^λ	-0.144***		
		(0.021)		
	ϕ_2^λ	0.080		
		(0.057)		
$\alpha, \alpha^+, \alpha^-$		0.587***	0.571***	0.605***
		(0.009)	(0.010)	(0.012)
Log-likelihood		-59,334	-25,485	-27,937
Parameters		48	21	21
Individuals		493	493	493
Observations		30,566	13,804	13,804

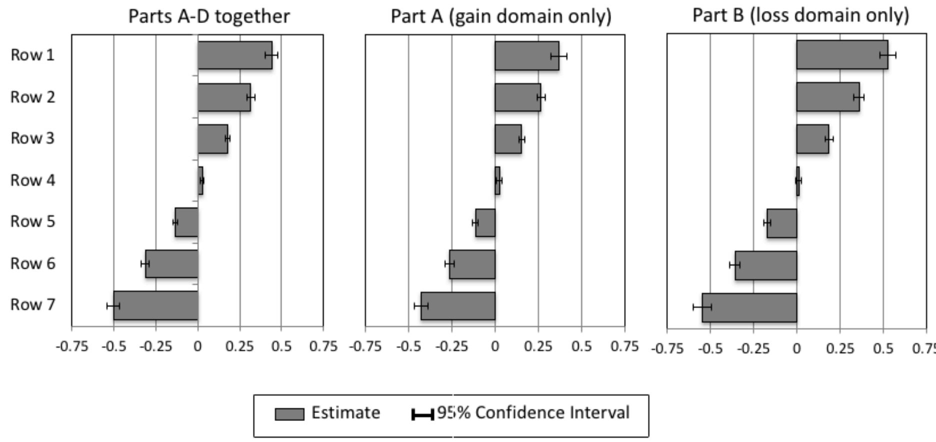
NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 4 in the main text, except that the results were obtained by estimating the CPT model with T&K's probability weighting function.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

6 Results of Robustness Check with CPT Model with CARA Utility

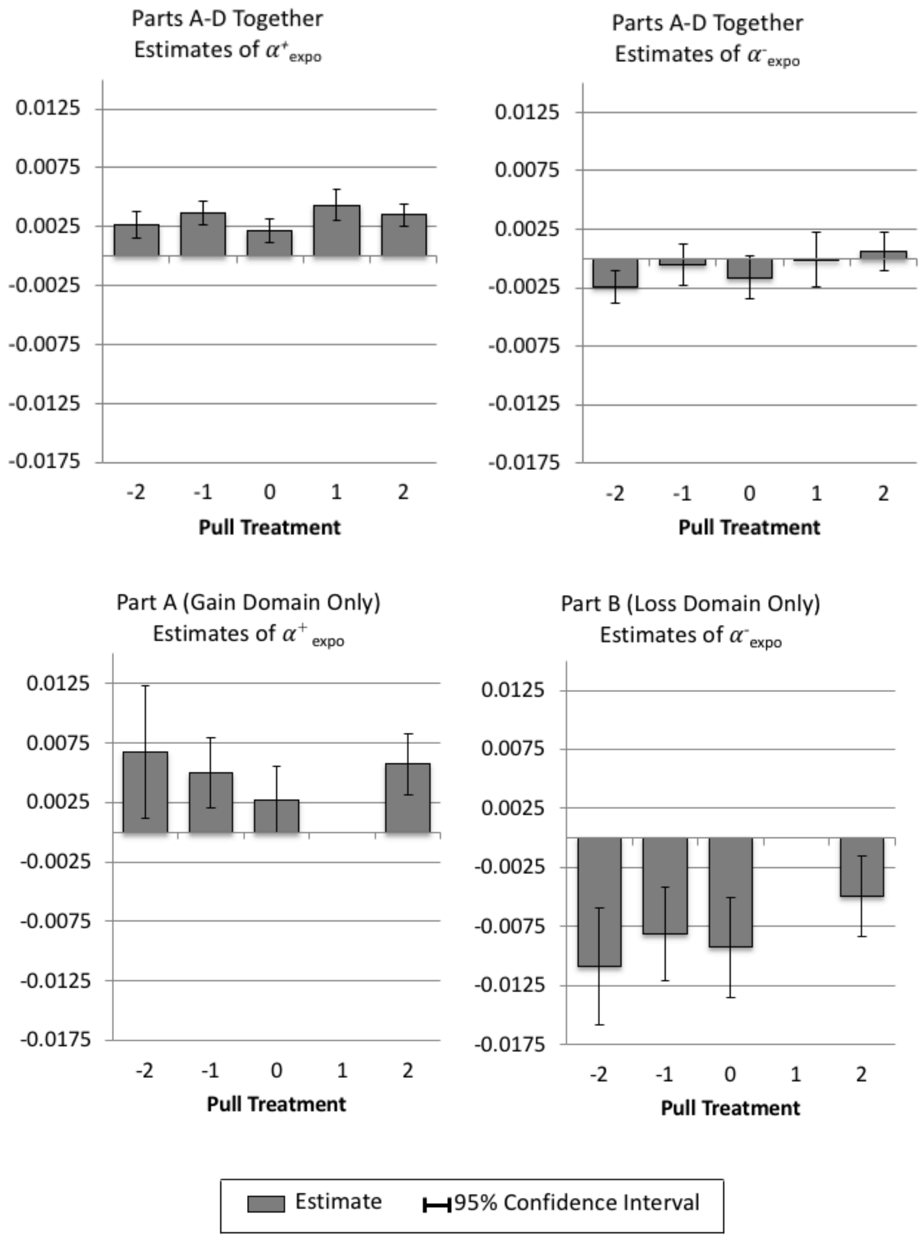
As a robustness check, we estimated the CPT model with CARA (a.k.a. "exponential") utility (Köbberling and Wakker 2005), $u(x) = \frac{1-e^{-\alpha_{expo}^{+}x}}{\alpha_{expo}^{+}}$ if $x \geq 0$, $u(-x) = \frac{1-e^{-\alpha_{expo}^{-}|x|}}{\alpha_{expo}^{-}}$ if $x < 0$, instead of with CRRA utility. As in the baseline model, we used the Prelec (1998) probability weighting function.

For this robustness check with CARA utility, unlike for the baseline CPT model with CRRA utility, we did not impose the assumption that the parameters for the coefficient of (absolute) risk aversion in the gain and in the loss domains are equal to one another (i.e., we did not assume that $\alpha_{expo}^{+} = \alpha_{expo}^{-}$). As Wakker (2010, section 9.6) and Köbberling and Wakker (2005) point out, with CRRA utility, for any λ there exists a range of x values for which 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 *smaller* than 1, which is the opposite of loss aversion. This issue does not arise with CARA utility, which makes the interpretation of λ in the CPT model with CARA utility with $\alpha_{expo}^{+} \neq \alpha_{expo}^{-}$ less problematic. (A second issue that arises with both CRRA and CARA utility when assuming different risk aversion parameters in the gain and loss domains is that 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; this issue also arises with the CPT model with CARA utility, thus making the estimates of λ we report below in this section more difficult to interpret.)

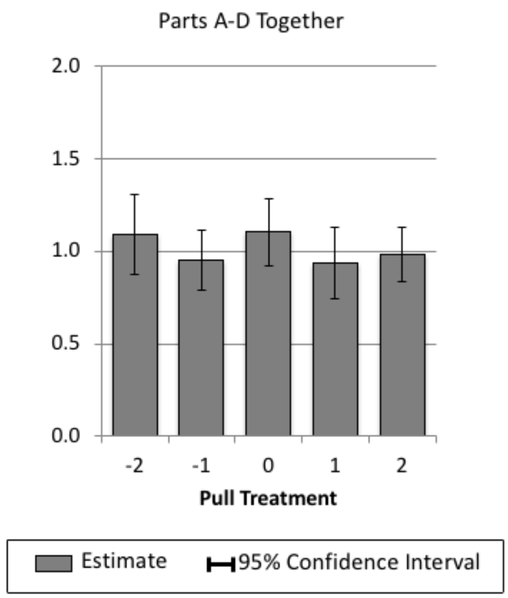
Online Appendix Figures 8.1-8.5 and Online Appendix Tables 8.1-8.4 below are analogous to Figures 2-6 and Tables 1-4 in the main text, respectively, except that the results were obtained by estimating the CPT model with CARA utility.



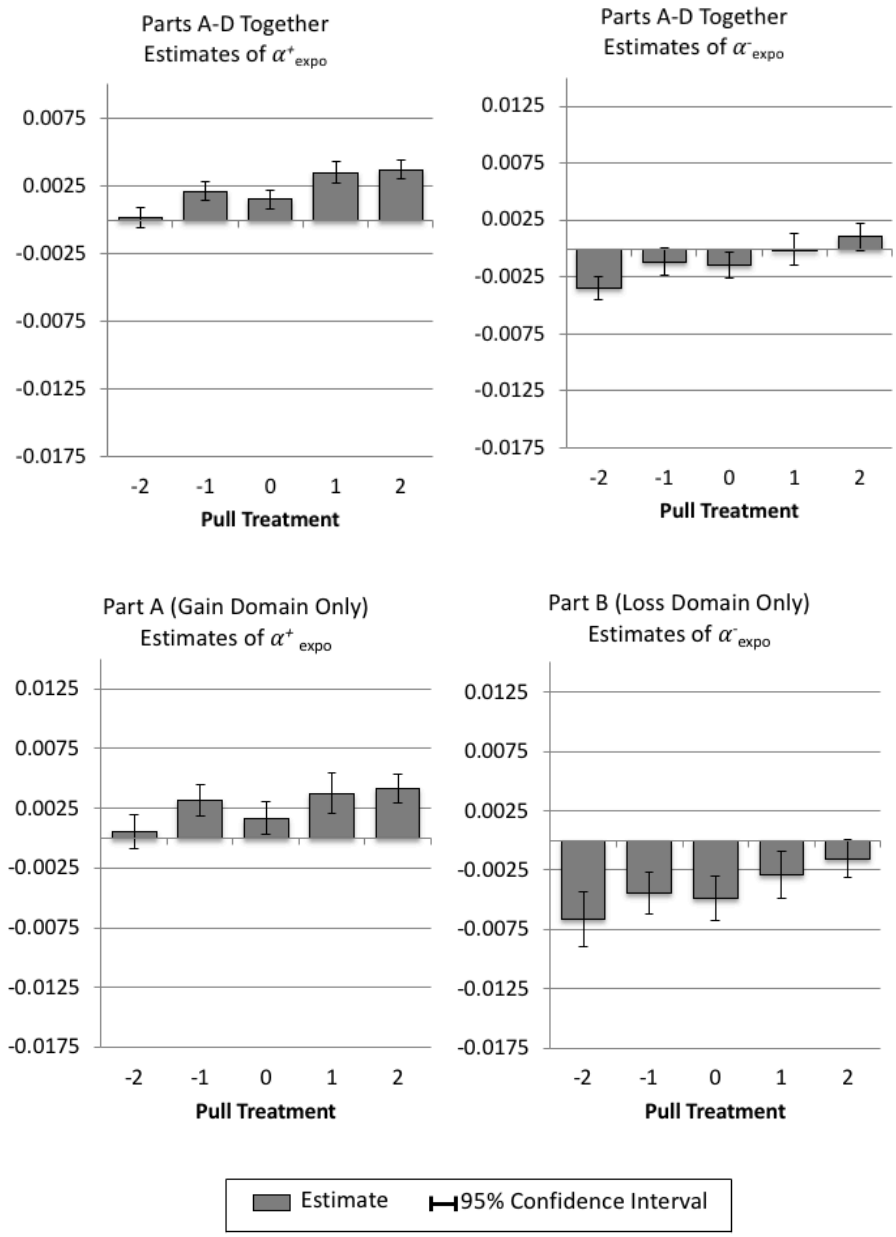
Online Appendix Figure 6.1. Implied estimates of the parameters for the compromise effect c_i as a function of the row i in which a choice appears. This figure is analogous to Figure 2 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.



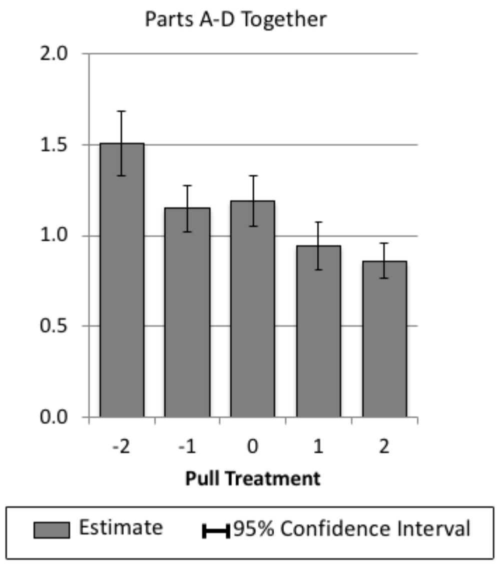
Online Appendix Figure 6.2. Estimates of α^{+}_{expo} and α^{-}_{expo} by Pull treatment, from the model with the compromise effect. This figure is analogous to Figure 3 in the main text, except that the results were obtained by estimating the CPT model with CARA utility. We omit the estimates for Pull Treatment 1 in the bottom two panels (Part A only and Part B only) because the MLE algorithm did not converge for these.



Online Appendix Figure 6.3. Estimates of λ by Pull treatment from the model with the compromise effect, for Parts A-D together. This figure is analogous to Figure 4 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.



Online Appendix Figure 6.4. Estimates of α^{+}_{expo} and α^{-}_{expo} by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 5 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.



Online Appendix Figure 6.5. Estimates of λ by Pull treatment from the model without the compromise effect, for Parts A-D together. This figure is analogous to Figure 6 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.

Online Appendix Table 6.1. ML Estimates of Selected Parameters in the Model with the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
α^{+}_{expo}	0.0034***	0.0054***	
	(0.0002)	(0.0007)	
α^{-}_{expo}	-0.0008*		-0.0065***
	(0.0004)		(0.0008)
λ	0.992***		
	(0.040)		
$\alpha, \alpha^{+}, \alpha^{-}$	0.638***	0.592***	0.694***
	(0.016)	(0.016)	(0.019)
$\beta, \beta^{+}, \beta^{-}$	1.331***	1.184***	1.72***
	(0.027)	(0.036)	(0.074)
π_1	-0.105***	-0.084***	-0.160***
	(.012)	(0.018)	(0.018)
π_2	-0.007***	-0.006***	-0.002
	(0.001)	(0.002)	(0.002)
Log-likelihood	-55,410	-24,321	-25,294
Wald test for π_1, π_2	$p < 1\times10^{-151}$	$p < 1\times10^{-95}$	$p < 1\times10^{-126}$
Parameters	20	10	10
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 1 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 6.2. ML Estimates of Selected Parameters in the Parameterized Model with the Compromise Effect

		Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
α_{expo}^{+}	$\alpha_{expo,0}^{+}$	0.0034***	0.0067***	
		(0.0004)	(0.0012)	
	$\phi_1^{\alpha_{expo}^{+}}$	0.0001	-0.0010	
		(0.0002)	(0.0006)	
	$\phi_2^{\alpha_{expo}^{+}}$	-0.0001	-0.0014	
		(0.0006)	(0.0014)	
α_{expo}^{-}	$\alpha_{expo,0}^{-}$	-0.0003		-0.0059***
		(0.0006)		(0.0010)
	$\phi_1^{\alpha_{expo}^{-}}$	0.0006**		0.0006
		(0.0003)		(0.0004)
	$\phi_2^{\alpha_{expo}^{-}}$	-0.0009		-0.0009
		(0.0008)		(0.0010)
λ	λ_0	0.973***		
		(0.056)		
	ϕ_1^{λ}	-0.015		
		(0.027)		
	ϕ_2^{λ}	0.037		
		(0.081)		
$\alpha_0, \alpha_0^{+}, \alpha_0^{-}$		0.572***	0.533***	0.626***
		(0.020)	(0.021)	(0.025)
$\beta_0, \beta_0^{+}, \beta_0^{-}$		1.35***	1.150***	1.74***
		(0.040)	(0.057)	(0.103)
π_1		-0.102***	-0.094***	-0.155***
		(0.012)	(0.018)	(0.018)
π_2		-0.007***	-0.005***	-0.003
		(0.001)	(0.002)	(0.002)
Log-likelihood		-55,246	-24,234	
Wald test for π_1, π_2		$p < 1\times10^{-146}$	$p < 1\times10^{-105}$	$p < 1\times10^{-121}$
Parameters		56	26	26
Individuals		493	493	493
Observations		30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 2 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 6.3. ML Estimates of Selected Parameters in the Model Without the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
α^{+}_{expo}	0.0021***	0.0023***	
	(0.0002)	(0.0003)	
α^{-}_{expo}	-0.0013***		-0.0045***
	(0.0003)		(0.0004)
λ	1.098***		
	(0.032)		
$\alpha, \alpha^{+}, \alpha^{-}$	0.587***	.554***	0.632***
	(0.010)	(0.011)	(0.012)
$\beta, \beta^{+}, \beta^{-}$	1.309***	1.260***	1.503***
	(0.017)	(0.023)	(0.036)
Log-likelihood	-60,099	-26,197	-27,953
Parameters	18	8	8
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 3 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 6.4. ML Estimates of Selected Parameters in the Parameterized Model Without the Compromise Effect

		Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
α^{+}_{expo}	$\alpha^{+}_{expo,0}$	0.0023***	0.0031***	
		(0.0003)	(0.0004)	
	$\phi_1^{\alpha^{+}_{expo}}$	0.0008***	0.0010***	
		(0.0001)	(0.0003)	
	$\phi_2^{\alpha^{+}_{expo}}$	-0.0001	-0.0012*	
		(0.0004)	(0.0006)	
α^{-}_{expo}	$\alpha^{-}_{expo,0}$	-0.0006*		-0.0036***
		(0.0004)		(0.0005)
	$\phi_1^{\alpha^{-}_{expo}}$	0.0009***		0.0011***
		(0.0002)		(0.0002)
	$\phi_2^{\alpha^{-}_{expo}}$	-0.0008*		-0.0009
		(0.0005)		(0.0006)
λ	λ_0	1.115***		
		(0.042)		
	ϕ_1^{λ}	-0.141***		
		(0.021)		
	ϕ_2^{λ}	0.021		
		(0.059)		
$\alpha_0, \alpha_0^{+}, \alpha_0^{-}$		0.547***	0.514***	0.590***
		(0.013)	(0.015)	(0.016)
$\beta_0, \beta_0^{+}, \beta_0^{-}$		1.312***	1.245***	1.49***
		(0.024)	(0.033)	(0.047)
Log-likelihood		-59,571	-26,003	-27,712
Parameters		54	24	24
Individuals		493	493	493
Observations		30,566	13,804	13,804

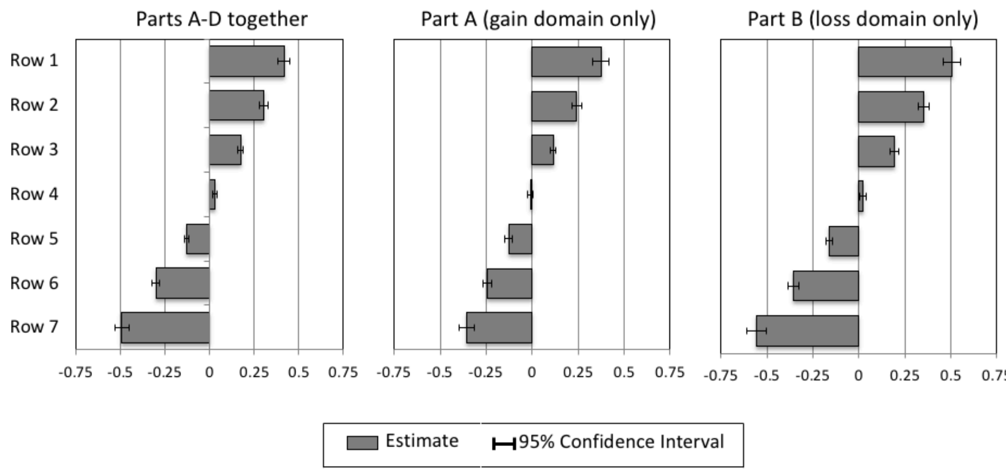
NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 4 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

7 Results of Robustness Check with CPT Model with Expo-Power Utility

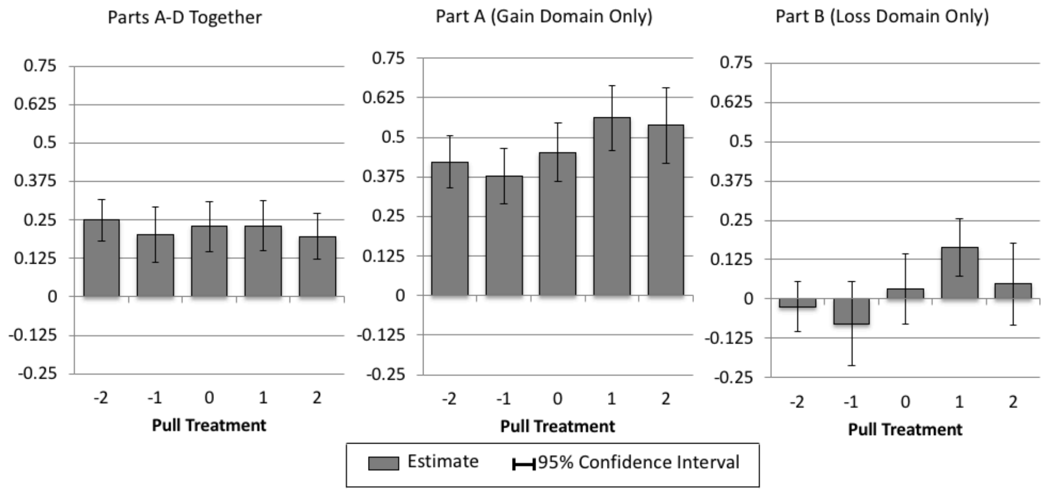
As a robustness check, we estimated the CPT model with expo-power utility (Saha 1993), $u(x) = \frac{1-e^{-\alpha_{e-p}x^{1-\gamma_{e-p}}}}{\alpha_{e-p}}$, instead of with CRRA utility. As in the baseline model, we used the Prelec (1998) probability weighting function.

Online Appendix Figures 9.1-9.9 and Online Appendix Tables 9.1-9.4 below are analogous to Figures 2-6 and Tables 1-4 in the main text, respectively, except that the results were obtained by estimating the CPT model with expo-power utility.

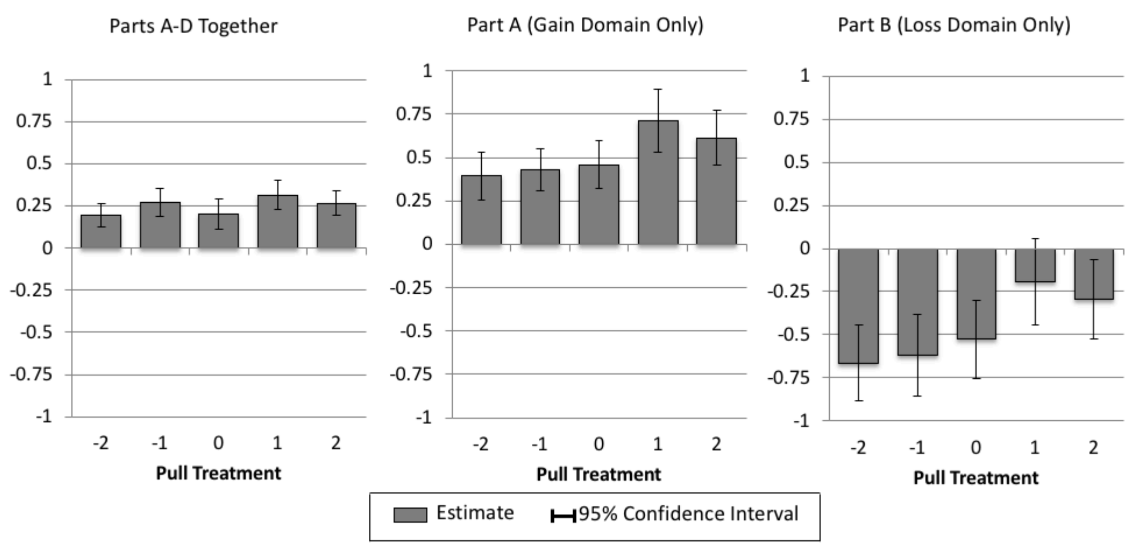
It is difficult to interpret the effects of the Pull treatment on the parameters of expo-power utility because both γ_{e-p} and α_{e-p} capture risk aversion. To see this, note that the Arrow-Pratt coefficient of relative risk aversion is $\frac{-u''(x)x}{u'(x)} = \gamma_{e-p} + \alpha_{e-p}\left(1-\gamma_{e-p}\right)x^{1-\gamma_{e-p}}$, which depends on both γ_{e-p} and α_{e-p}. As a result, γ_{e-p} and α_{e-p} may move together across Pull treatments in complicated ways, and there is no clear theoretical relationship between γ_{e-p}, α_{e-p} and Pull treatment. For that reason, in Online Appendix Figures 9.2-9.4 and 9.6-9.8, we report estimates of the coefficient of relative risk aversion with $x = 10$, 50, and 200 by Pull treatment (instead of estimates of γ_{e-p} and α_{e-p} by Pull treatment). Also, in Online Appendix Tables 7.2 and 7.4, we only report the results of parameterized model for Parts A-D together, since it is only meaningful to interpret the effect of the Pull treatment on the parameter λ (and we can only estimate λ using data from Parts A-D together).



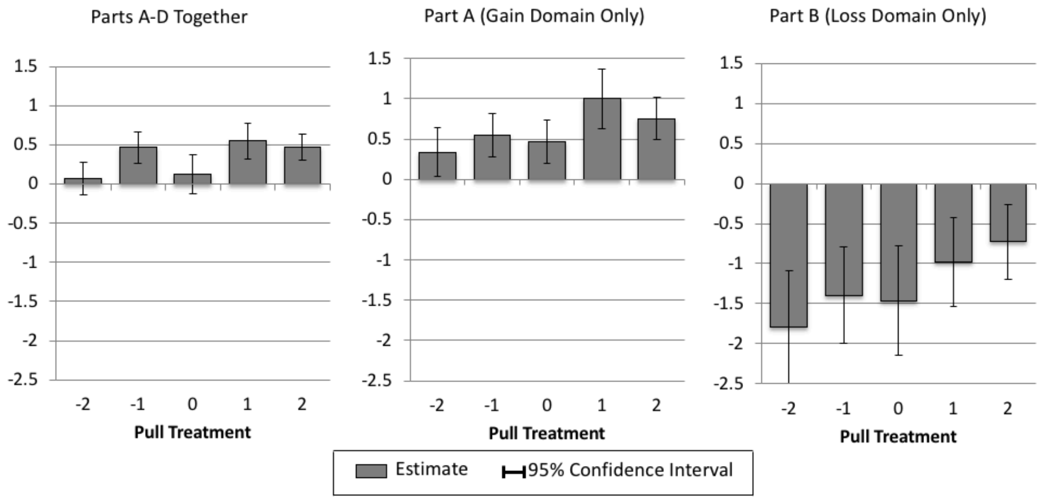
Online Appendix Figure 7.1. Implied estimates of the parameters for the compromise effect c_i as a function of the row i in which a choice appears. This figure is analogous to Figure 2 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility.



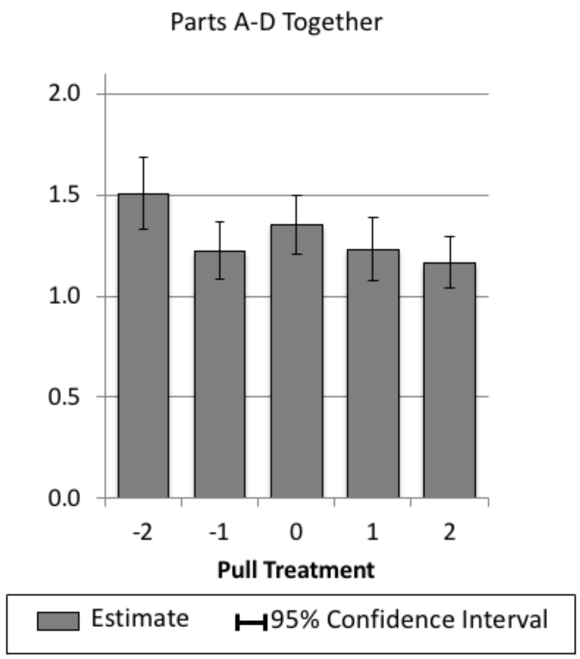
Online Appendix Figure 7.2. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 10) by Pull treatment, from the model with the compromise effect. This figure is analogous to Figure 3 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



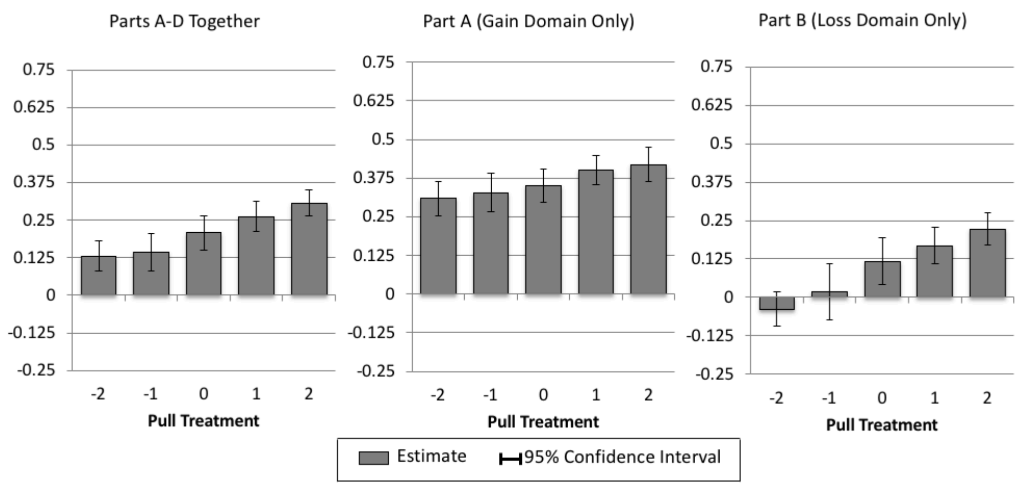
Online Appendix Figure 7.3. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 50) by Pull treatment, from the model with the compromise effect. This figure is analogous to Figure 3 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



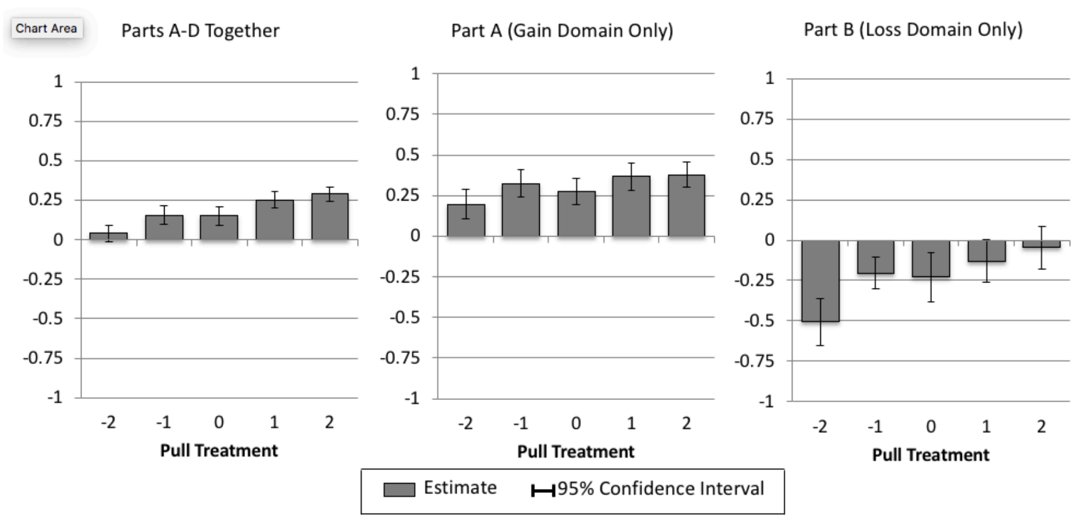
Online Appendix Figure 7.4. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 200) by Pull treatment, from the model with the compromise effect. This figure is analogous to Figure 3 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



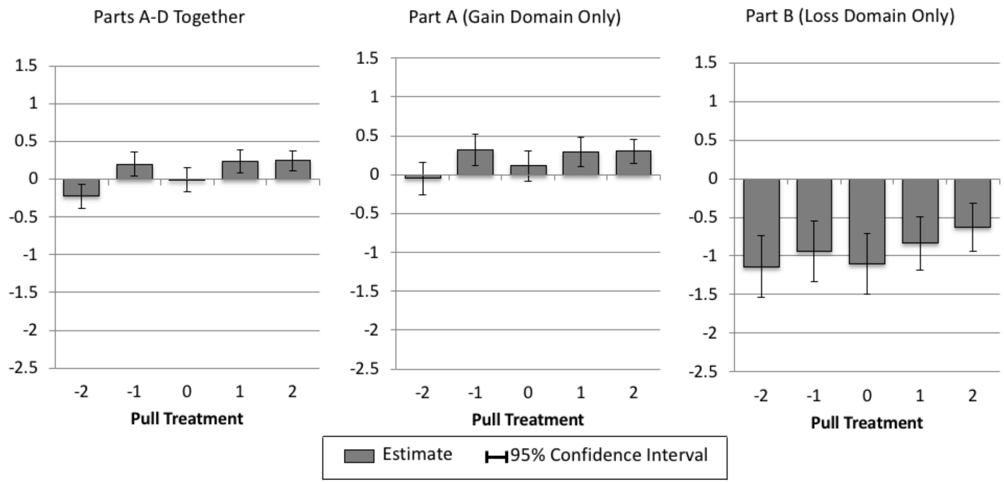
Online Appendix Figure 7.5. Estimates of λ by Pull treatment from the model with the compromise effect, for Parts A-D together. This figure is analogous to Figure 4 in the main text, except that the results were obtained by estimating the CPT model with CARA utility.



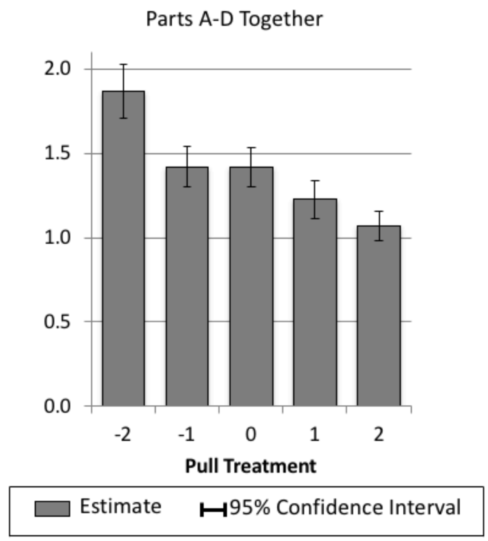
Online Appendix Figure 7.6. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 10) by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 5 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



Online Appendix Figure 7.7. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 50) by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 5 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



Online Appendix Figure 7.8. Estimates of the Arrow-Pratt coefficient of relative risk aversion (with x = 200) by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 5 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. We report the Arrow-Pratt coefficient of relative risk aversion instead of the estimates of γ_{e-p} and α_{e-p} because both γ_{e-p} and α_{e-p} capture risk aversion and may move together in complicated ways across Pull treatments.



Online Appendix Figure 7.9. Estimates of λ by Pull treatment from the model without the compromise effect, for Parts A-D together. This figure is analogous to Figure 6 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility.

Online Appendix Table 7.1. ML Estimates of Selected Parameters in the Model with the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma_{e-p}, \gamma_{e-p}^{+}, \gamma_{e-p}^{-}$	0.219***	0.427***	0.677***
	(0.020)	(0.020)	(0.044)
$\alpha_{e-p}, \alpha_{e-p}^{+}, \alpha_{e-p}^{-}$	0.0025**	0.0116**	-0.9687***
	(0.0010)	(0.0054)	(0.3114)
λ	1.288***		
	(0.034)		
$\alpha, \alpha^{+}, \alpha^{-}$	0.622***	0.566***	0.679***
	(0.015)	(0.015)	(0.018)
$\beta, \beta^{+}, \beta^{-}$	1.112***	0.837***	1.67***
	(0.025)	(0.037)	(0.075)
π_1	-0.091***	-0.137***	-0.136***
	(0.012)	(0.018)	(0.019)
π_2	-0.008***	0.002	-0.005**
	(0.001)	(0.002)	(0.002)
Log-likelihood	-55,374	-23,912	-25,264
Wald test for π_1, π_2	$p < 1\times10^{-146}$	$p < 1\times10^{-79}$	$p < 1\times10^{-123}$
Parameters	20	11	11
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 1 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 7.2. ML Estimates of Selected Parameters in the Parameterized Model with the Compromise Effect

		Parts A-D Together
$\gamma_{e-p,0}$		0.175***
		(0.029)
$\alpha_{e-p,0}$		0.0032***
		(0.0010)
λ	λ_0	1.234***
		(0.049)
	ϕ_1^λ	-0.066**
		(0.026)
	ϕ_2^λ	0.105
		(0.069)
α_0		0.559***
		(0.019)
β_0		1.168***
		(0.037)
π_1		-0.089***
		(0.012)
π_2		-0.008***
		(0.001)
Log-likelihood		-55,210
Wald test for π_1, π_2		$p < 1\times10^{-138}$
Parameters		56
Individuals		493
Observations		30,566

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. The Wald test is for the joint significance of π_1 and π_2. This table is analogous to Table 2 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. Both γ_{e-p} and α_{e-p} capture risk aversion and may move together across Pull treatments in complicated ways, and as a result only estimates related to λ are meaningful in the parameterized model with expo-power utility. We thus only report the results for Parts A-D together.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 7.3. ML Estimates of Selected Parameters in the Model Without the Compromise Effect

	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain Only)
$\gamma_{e-p}, \gamma_{e-p}^{+}, \gamma_{e-p}^{-}$	0.244***	0.415***	0.331***
	(0.016)	(0.017)	(0.103)
$\alpha_{e-p}, \alpha_{e-p}^{+}, \alpha_{e-p}^{-}$	-0.0046***	-0.0210***	-0.0616
	(0.0015)	(0.0059)	(0.0512)
λ	1.375***		
	(0.030)		
$\alpha, \alpha^{+}, \alpha^{-}$	0.574***	0.538***	0.637***
	(0.010)	(0.011)	(0.012)
$\beta, \beta^{+}, \beta^{-}$	1.133***	0.992***	1.476***
	(0.016)	(0.022)	(0.051)
Log-likelihood	-59,933	-25,580	-27,840
Parameters	18	9	9
Individuals	493	493	493
Observations	30,566	13,804	13,804

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 3 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Online Appendix Table 7.4. ML Estimates of Selected Parameters in the Parameterized Model Without the Compromise Effect

		Parts A-D Together
$\gamma_{e-p,0}$		0.213***
		(0.033)
$\alpha_{e-p,0}$		-0.0014
		(0.0032)
λ	λ_0	1.33***
		(0.045)
	ϕ_1^λ	-0.154***
		(0.021)
	ϕ_2^λ	0.112*
		(0.061)
α_0		0.535***
		(0.012)
β_0		1.149***
		(0.022)
Log-likelihood		-59,414
Parameters		54
Individuals		493
Observations		30,566

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. This table is analogous to Table 4 in the main text, except that the results were obtained by estimating the CPT model with expo-power utility. Both γ_{e-p} and α_{e-p} capture risk aversion and may move together across Pull treatments in complicated ways, and as a result only estimates related to λ are meaningful in the parameterized model with expo-power utility. We thus only report the results for Parts A-D together.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

8 Numerical Estimates of the Parameters for the Compromise Effect c_i as a Function of the Row i in Which a Choice Appears

Online Appendix Table 8.1 shows the numerical estimates of the parameters for the compromise effect c_i. These results are also shown graphically in Figure 2 of the paper.

Online Appendix Table 8.1. Estimates of the Parameters for the Compromise Effect c_i in the Model with the Compromise Effect, as a Function of the Row i in Which a Choice Appears

	Choice Appears		
	Parts A-D Together	Part A (Gain Domain Only)	Part B (Loss Domain only)
c_1	0.416***	0.371***	0.515***
	(0.018)	(0.023)	(0.023)
c_2	0.302***	0.242***	0.358***
	(0.012)	(0.013)	(0.015)
c_3	0.174***	0.116***	0.192
	(0.007)	(0.008)	(0.011)
c_4	0.030***	-0.007	0.017*
	(0.005)	(0.008)	(0.009)
c_5	-0.128***	-0.126***	-0.166***
	(0.007)	(0.009)	(0.009)
c_6	-0.302***	-0.242**	-0.358***
	(0.012)	(0.013)	(0.015)
c_7	-0.491***	-0.355***	-0.558***
	(0.020)	(0.020)	(0.027)

NOTE: The estimates of c_i were obtained by transforming the estimates of π_1 and π_2 from Table 1 of the paper, as described in the main text.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

9 Additional Information on the Analysis of the Demographic Correlates of the CPT Model and the Compromise Effect Parameters

As mentioned in Section 8 of the main text, we analyzed the demographic correlates of the four key parameters of the CPT model (γ, λ, α, β) and of the two model parameters that capture the compromise effect (π_1, π_2). Also as mentioned in Section 8 of the main text, in our baseline demographic specification, we estimate our CPT model with the compromise effect using data from Parts A-D together, with these six key model parameters specified as linear functions of a constant, age, sex, a dummy variable indicating whether one has a college degree, SAT Math score, the log of one's parents' combined annual income, as well as dummy variables to control for race. In other words, we substitute γ in the utility function in equation (1) of the main text by:

$$\gamma = \gamma_0 + \phi^{\gamma}_{\text{age}} age + \phi^{\gamma}_{\text{sex}} sex + \phi^{\gamma}_{\text{college}} college + \phi^{\gamma}_{\text{SAT}} SAT\_Math$$
$$+\phi^{\gamma}_{\text{inc.}} \log\left(parental\_income\right) + \boldsymbol{\phi}^{\boldsymbol{\gamma}}_{\mathbf{Other}} \boldsymbol{Other\_variables},$$

where $\boldsymbol{Other\_variables}$ includes the dummy variables that control for race as well as dummy variables that indicate missing observations for each variable that has missing observations. We also substituted λ, α, β, π_1, and π_2 with analogous parametrized equations.

In addition, we estimated several specifications to verify the robustness of the results from our baseline demographic specification. First, we estimated the baseline demographic specification again, but using data from Part A only, and then using data from Part B only. Second, we estimated a specification akin to the baseline demographic specification using data from Parts A-D together, but with CARA (a.k.a. "exponential") utility (Köbberling and Wakker 2005) (instead of CRRA, a.k.a. "power", utility). As in Online Appendix Section 6, we did not impose the assumption that the parameters for the coefficient of (absolute) risk aversion in the gain and in the loss domains (i.e., α^{+}_{expo} and α^{-}_{expo}, as well as the corresponding parameterized equations) are equal to one another in this specification with CARA utility. Lastly, we employed a two-step procedure in which we first estimated our baseline CPT model with the compromise effect separately for each participant, and then regressed each estimated parameter of interest on the demographic variables (and on the variables included in $\boldsymbol{Other\_variables}$). One limitation of this two-step analysis is that, to ensure that the MLE algorithm converged for sufficiently many participants, we had to reduce the number of parameters in the model by assuming that σ_q is identical across all screens.[1]

We dropped from this analysis data from approximately three dozens of participants who had not provided their age, sex, and/or their highest level of education (unless they

[1] With this assumption, the MLE algorithm still failed to converge for 40 participants; we further dropped from the regression analysis in the second step 35 participants for whom the estimates of the parameter σ_q were particularly large; this left 408 participants for the regression analysis, vs. 458 participants whose data were used in the other demographic specifications (as discussed below).

indicated they were still currently studying). As in all the other analyses reported in the paper, we also dropped from this analysis data from the 28 participants for whom the MLE algorithm does not converge when the CPT model is estimated separately for each participant (in the model without the compromise effect, using data from Parts A-D together, and assuming that σ_q is identical across all screens). This left 458 participants whose data were included in this analysis.

The dummy variables that control for race comprise a dummy variable that is equal to 1 if one's self-reported ethnicity is "Asian", as well as another dummy variable that is equal to 1 if one's self-reported ethnicity is "African-American", "Hispanic", "Native American", or "Other". Most participants for whom these dummies are both equal to 0 reported that their ethnicity is "Caucasian", but a few of these participants did not report their ethnicity.

The dummy variable indicating whether one has a college degree was defined based on responses to the question "what is the highest level of education you have completed?", with the five possible response categories "Additional education beyond college", "Completed college", "Some college", "Completed high school or GED", "Some high school". Participants who responded "Additional education beyond college" or "Completed college" were coded as having completed college. Only participants who were not fulltime students were asked this education question, so many observations are missing for our college dummy variable. Instead of dropping the corresponding participants from this analysis, we coded the college dummy as a constant ("-9") for these participants, and included in the parameterized equations for the parameters of interest another dummy variable indicating whether each participant has missing data for the college variable.

Many participants also had missing data for the SAT Math and the log parental income variables. We similarly coded these variables as constants for these participants and included, in the parameterized equations for the parameters of interest, dummy variables indicating whether each participant has missing data for these variables.

Only respondents who reported being full-time students were asked their parents' combined annual income. The log parental income variable was constructed from responses to the question "If you are a full-time student, what is your best guess of your parents' combined annual income?", with possible response categories "Under $20,000", "Between $20,000 and $39,999", "Between $40,000 and $59,999", "Between $60,000 and $79,999", "Between $80,000 and $99,999", and "Over $100,000". We replaced these responses with the midpoint of each interval (e.g., we coded parental income for participants who responded "Between $20,000 and $39,999" as $30,000); for the participants who responded "Under $20,000" and "Over $100,000", we replaced these responses with "$15,000" and "125,000", respectively. Then, we took the logarithm of the resulting variable.

Online Appendix Table 9.1 shows summary statistics for these variables.

Online Appendix Table 9.1. Summary Statistics for the Demographic Covariates

	N	*Mean*	*SD*	*Min*	*Max*
Age	458	27.0	10.9	18	67
Female	458	0.62	0.49	0	1
College	190	0.65	0.48	0	1
SAT Math	328	670	111	200	800
Parental income	237	81,139	40,371	15,000	125,000
Asian	458	0.24	0.43	0	1
Other race	458	0.14	0.35	0	1

NOTE: Additional details on the variables can be found in the text. "Other race" is a dummy variable that is equal to 1 if one reported that one's ethnicity is "African-American", "Hispanic", "Native American", or "Other".

Online Appendix Table 9.2 reports the estimates of the parameters of interest in the baseline demographic specification.

Online Appendix Table 9.2. ML Estimates of Selected Parameters in the Baseline Demographic Specification

	γ	λ	α	β	π_1	π_2
Age	0.0008	-0.0052	0.0027	-0.0004	0.0031**	-0.0002
	(0.0009)	(0.0039)	(0.0024)	(0.0027)	(0.0013)	(0.0002)
Female	0.017	0.090	0.024	-0.016	0.023	-0.003
	(0.013)	(0.058)	(0.029)	(0.031)	(0.026)	(0.003)
College	0.000	-0.029	-0.062	0.030	-0.003	-0.003
	(0.023)	(0.097)	(0.054)	(0.067)	(0.040)	(0.004)
SAT Math	-0.00036***	0.00127***	0.00013	0.00014	-0.00025**	0.00003*
	(0.00009)	(0.00029)	(0.00021)	(0.00026)	(0.00011)	(0.00002)
log(parental income)	-0.002	-0.038	0.031	0.013	-0.024	0.000
	(0.012)	(0.064)	(0.028)	(0.037)	(0.030)	(0.003)
Log-likelihood	-50,659					
Parameters	79					
Individuals	458					
Observations	28,396					

NOTE: Standard errors are clustered by participant. The log-likelihood statistic is for the model without clustering. All estimates were obtained from one MLE. The estimates in each column indicate the effects of selected demographic covariates on the parameter at the top of the column.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

The estimates from the robustness specifications are available upon request. (We note that the MLE algorithm for the robustness specification that is identical to the baseline demographic specification but only uses data from Part A failed to converge; however, after 2,000 iterations, the estimates were consistent with those from the baseline and other robustness specifications.)

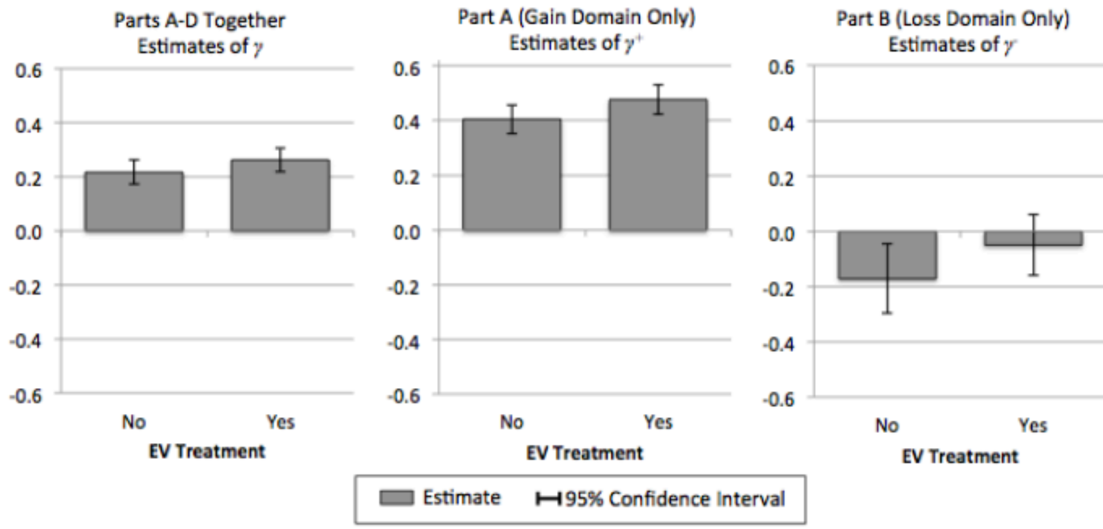
As mentioned in the main text, two results stand out across the baseline and robustness specifications. First, higher SAT Math scores are associated with lower γ—i.e., with lower risk aversion in the gain domain and higher risk aversion (or, equivalently, lower risk seeking) in the loss domain. Second, higher SAT Math scores are associated with *higher* loss aversion (λ). As discussed in the main text, the first result is consistent with the existing literature, while the second is not. The parameter estimates in Online Appendix Table 9.2 imply that a 100-point increase in the SAT Math score is associated with a 0.036-unit increase in the coefficient of relative risk aversion (γ), and a 0.127-unit *increase* in the loss aversion parameter (λ); by comparison our estimates of γ and λ in our baseline CPT model with the compromise effect are 0.242 and 1.311, respectively (from Table 1 of the main text).

While SAT scores are significantly associated with π_1 and marginally significantly associated with π_2, when considering the compromise effect parameters c_i (where i denotes the row of the alternative prospect on the screen, $i = 1,2,\ldots,7$), these two effects cancel out. To see, recall that $c_i = \pi_1(i-4) + \pi_2(i^2-20)$. It follows that

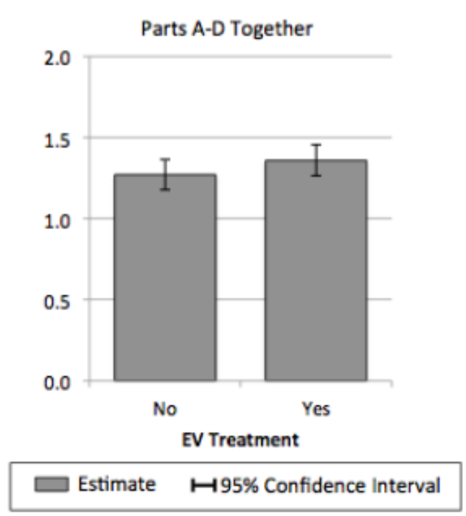
$$\frac{dc_i}{dSAT} = \frac{\partial c_i}{\partial \pi_1}\frac{\partial \pi_1}{\partial \mathrm{SAT}} + \frac{\partial c_i}{\partial \pi_2}\frac{\partial \pi_2}{\partial \mathrm{SAT}} = (i-4)\phi_{SAT}^{\pi_1} + (i^2-20)\phi_{SAT}^{\pi_2}.$$

Thus, in the first and last (i.e., seventh) rows, $\frac{dc_1}{dSAT} = -3\phi_{SAT}^{\pi_1} - 19\phi_{SAT}^{\pi_2}$, and $\frac{dc_2}{dSAT} = 3\phi_{SAT}^{\pi_1} + 29\phi_{SAT}^{\pi_2}$. Across both the baseline and the robustness specifications, $\phi_{SAT}^{\pi_1} \approx 10\times\phi_{SAT}^{\pi_2}$, and so the effects of SAT Math scores on π_1 and π_2 effectively cancel out when considering the net effect of SAT Math scores on the compromise effect.

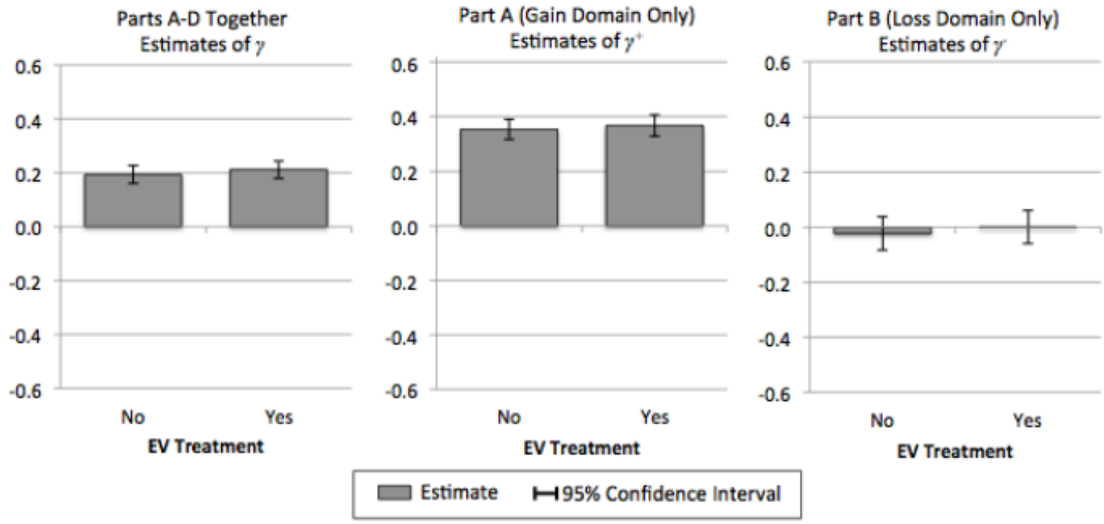
10 Estimates of γ, γ^{+}, γ^{-}, and λ by EV Treatment in the Models with and Without the Compromise Effect



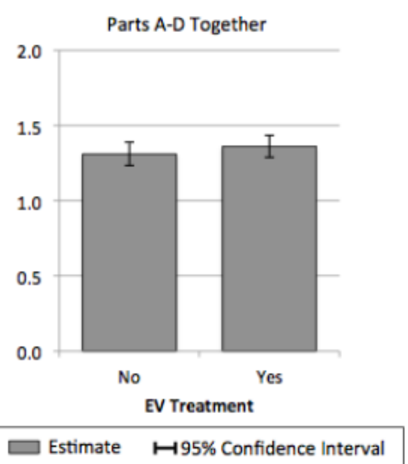
Online Appendix Figure 10.1. Estimates of γ, γ^{+}, and γ^{-} by EV treatment, from the model with the compromise effect. The negative estimates of γ^{-} for Part B reflect risk aversion in the loss domain, unlike what CPT predicts. (γ is not estimated for Parts C and D only because these parts have few questions.)



Online Appendix Figure 10.2. Estimates of λ by EV treatment, from the model with the compromise effect, for Parts A-D together. (λ cannot be estimated for Part A only or Part B only because the questions in these parts are all in the gain or loss domains, and is not estimated for Parts C and D only because these parts have few questions.)



Online Appendix Figure 10.3. Estimates of γ, γ^+, and γ^- by EV treatment, from the model without the compromise effect. This figure is analogous to Online Appendix Figure 10.1, except that the estimated model does not control for the compromise effect.



Online Appendix Figure 10.4. Estimates of λ by EV treatment, from the model without the compromise effect, for Parts A-D together. This figure is analogous to Online Appendix Figure 10.2, except that the estimated model does not control for the compromise effect.

11 Stata Code to Estimate the Baseline CPT Model with the Compromise Effect

We include below the Stata code used to estimate the baseline CPT model (with CRRA utility and the Prelec (1998) probability weighting function) with the compromise effect, using the data from Parts A-D and from all treatments together. The variable names in the code match the notation used in the main text.

Upon publication of the paper, we will post online the Stata code to estimate the other baseline CPT specifications that use the data from Parts A-D together (including specifications without the compromise effect, specifications that estimate the model for each treatment separately, and specifications with parameterized models). We will also post online the analogous specifications used for the three main sets of robustness checks which we describe in Section 3.4 of the main text. In addition, we will post online the de-identified choice data we collected in the experiment. (To ensure the privacy of the participants is not compromised, we will not post the data from the brief post-experiment questionnaire.)

Stata code:

```
*****************************************************************************************************************
*
* This .do file estimates the parameters of the following specification:
*       - Baseline model:
*               + constant relative risk aversion (CRRA) utility
*               + Prelec probability weights
*       - Includes controls for the compromise effect
*       - The model is estimated using data from all Parts (Parts A, B, C, & D) together
*
*****************************************************************************************************************


* Preliminaries

clear all
set more off, permanently
set memory 600m
set matsize 1000
set trace off

* INPUT FILE REQUIRED:  "Controlling for the Compromise Effect -- Choice data.dta"
* The input file must be located in the following working directory
cd "/User/Directory"


cap log close
log using "1a_CRRA_allParts_CompEffect.txt", text replace

timer clear 1
timer on 1


use "Controlling for the Compromise Effect -- Choice data.dta", clear

keep if notAnOutlier == 1

* Drop the questions designed by K&T to be placebo tests for loss aversion
drop if (gamble_index == 3 | gamble_index == 1) & part == "D"


******************************************************************
* Define the program

capture program drop myLogLikFcn
program myLogLikFcn

args lnf gamma alpha beta lambda       sA1 sA2 sA3 sA4 sA5   sB1 sB2 sB3 sB4 sB5  sC1 sC2 sD     pi1 pi2

tempvar weight_Xqf_high weight_Xqf_low weight_Xqi_high weight_Xqi_low weight_XqiPlus1_high weight_XqiPlus1_low ///
```

```
util_Xqf_high util_Xqf_low util_Xqi_high util_Xqi_low util_XqiPlus1_high util_XqiPlus1_low ///
c_i c_iPlus1 sigma ///
U_Pqf U_Pqi U_PqiPlus1


* Prelec weighting function w(`X') = exp( -`beta' * (-ln( `X' ))^`alpha' )
foreach X in Xqf_high Xqf_low Xqi_high Xqi_low XqiPlus1_high XqiPlus1_low {
        qui generate double `weight_`X'' = exp( -`beta' * (-ln( prob_`X' ))^`alpha' ) if prob_`X' != 0
        qui replace `weight_`X'' = 0 if prob_`X' == 0
}

* Constant relative risk aversion (CRRA) utility function u(`X') = `X'^(1-`gamma')/(1-`gamma')
foreach X in Xqf_high Xqf_low Xqi_high Xqi_low XqiPlus1_high XqiPlus1_low {
        qui generate double `util_`X'' = abs(`X')^(1-`gamma')/(1-`gamma')
}

* Compromise effect for rows i and i+1
qui generate double `c_i' = ((-4*`pi1' - 20*`pi2') + `pi1' * row_i + `pi2' * row_i^2)
qui generate double `c_iPlus1' = ((-4*`pi1' - 20*`pi2') + `pi1' * row_iPlus1 + `pi2' * row_iPlus1^2)


* Sigma parameter for each group of screens
qui generate double `sigma' = (`sA1'*qA1 + `sA2'*qA2 + `sA3'*qA3 + `sA4'*qA4 + `sA5'*qA5) if part == "A"
qui replace `sigma' = (`sB1'*qB1 + `sB2'*qB2 + `sB3'*qB3 + `sB4'*qB4 + `sB5'*qB5) if part == "B"
qui replace `sigma' = (`sC1' *qC1 + `sC2' *qC2) if part == "C"
qui replace `sigma' = (`sD' * qD ) if part == "D"


* Cumulative Prospect Theory (CPT) Value of the fixed prospect U(.)
qui generate double `U_Pqf' = ( `weight_Xqf_high' * `util_Xqf_high'  +  (1-`weight_Xqf_high') * `util_Xqf_low' ) ///
                              if ( Xqf_low >=0 & Xqf_high >= 0 )
               qui  replace  `U_Pqf'  =  (  -`weight_Xqf_low'  *  `lambda'  *  `util_Xqf_low'   -   (1-`weight_Xqf_low')  *
`lambda' * `util_Xqf_high' ) ///
                                                 if ( Xqf_low <=0 & Xqf_high <= 0 )
               qui  replace  `U_Pqf'  =  (    `weight_Xqf_high'  *  `util_Xqf_high'  -  `weight_Xqf_low'  *  `lambda'  *
`util_Xqf_low' ) ///
                                                         if ( Xqf_high > 0 & Xqf_low < 0 )

* CPT Value of the alternative prospect U(.) for choice i
qui generate double `U_Pqi' = ( `weight_Xqi_high' * `util_Xqi_high'  +  (1-`weight_Xqi_high') * `util_Xqi_low' ) ///
                              if ( Xqi_low >= 0 & Xqi_high >=0 )
               qui replace `U_Pqi' = ( -`weight_Xqi_low' * `lambda' * `util_Xqi_low' - (1-`weight_Xqi_low') * `lambda'
* `util_Xqi_high' ) ///
                                                 if ( Xqi_low <=0 & Xqi_high <= 0 )
               qui  replace  `U_Pqi'  =  (    `weight_Xqi_high'  *  `util_Xqi_high'  -  `weight_Xqi_low'  *  `lambda'  *
`util_Xqi_low' ) ///
                                                         if ( Xqi_high > 0 & Xqi_low < 0 )

* CPT Value of the alternative prospect U(.) for choice i+1
qui  generate  double  `U_PqiPlus1'  =  (  `weight_XqiPlus1_high'  *  `util_XqiPlus1_high'   +   (1-`weight_XqiPlus1_high')  *
`util_XqiPlus1_low' ) ///
                              if ( XqiPlus1_low >= 0 & XqiPlus1_high >= 0 )
               qui  replace  `U_PqiPlus1'  =  (  -`weight_XqiPlus1_low'  *  `lambda'  *  `util_XqiPlus1_low'    -    (1-
`weight_XqiPlus1_low') * `lambda' * `util_XqiPlus1_high' ) ///
                                                 if ( XqiPlus1_low <=0 & XqiPlus1_high <=0 )
               qui replace `U_PqiPlus1' = (   `weight_XqiPlus1_high' * `util_XqiPlus1_high' - `weight_XqiPlus1_low' *
`lambda' * `util_XqiPlus1_low' ) ///
                                                         if ( XqiPlus1_high > 0 & XqiPlus1_low < 0 )


* The Log Likelihood function
quietly replace `lnf' = ln( ///
                                               normal( ( `U_Pqi' - `U_Pqf' ) / `sigma' + `c_i' ) ///
                                               - normal( (`U_PqiPlus1' - `U_Pqf') / `sigma' + `c_iPlus1' ) ///
                                               )

quietly replace `lnf' = ln( ///
                                               1 - normal( (`U_PqiPlus1' - `U_Pqf') / `sigma' + `c_iPlus1' ) ///
                                               ) if Xqi_high == 99999

quietly replace `lnf' = ln( ///
                                               normal( (`U_Pqi' - `U_Pqf') / `sigma' + `c_i' ) ///
                                               ) if XqiPlus1_low == -99999

* The log likelihood function needs to be defined slightly differently when the alternative prospects are increasing
from (a) to (g).
* We subtract the compromise effect here because theoretically, c_iPlus1 > c_i when the alternative prospects are
increasing.

quietly replace `lnf' = ln( ///
                                               normal( ( `U_PqiPlus1' - `U_Pqf' ) / `sigma' - `c_iPlus1' ) ///
                                               - normal( (`U_Pqi' - `U_Pqf') / `sigma' - `c_i' ) ///
                                               ) if increasing == 1

quietly replace `lnf' = ln( ///
                                               1 - normal( (`U_Pqi' - `U_Pqf') / `sigma' - `c_i' ) ///
                                               ) if XqiPlus1_high == 99999 & increasing == 1

quietly replace `lnf' = ln( ///
                                               normal( (`U_PqiPlus1' - `U_Pqf') / `sigma' - `c_iPlus1' ) ///
                                               ) if Xqi_low == -99999 & increasing == 1


end
```

```
**************************************************
* Estimate the model

ml model lf myLogLikFcn /gamma /alpha /beta /lambda  /sA1 /sA2 /sA3 /sA4 /sA5    /sB1 /sB2 /sB3 /sB4 /sB5  /sC1 /sC2
/sD   /pi1 /pi2, technique(nr) vce(cluster subjectNo)


* Initial values from 2a_CRRA_allParts.do
* Set the initial values for pi1 and pi2 equal to 0
* We use these initial values to ensure that the MLE algorithm converges
ml init .2032829 .5742116 1.123415 1.336532       5.708492 9.633632 10.28813 16.67078  40.8376        9.962839 14.34956
13.56126  18.37935  35.11294       6.672186 17.22844     9.602023     0 0, copy


capture noisily ml maximize, difficult showtolerance trace gradient iterate(500)
* capture noisily ml maximize, difficult showtolerance trace gradient iterate(500) coeflegend


******************************************************************
* Wald test for the joint significance of pi1, pi2
* W = Theta^' * ( R(Theta^) * Var^(Theta^) * R'(Theta^) )^-1 * Theta^
* Here, Theta = [pi1, pi2] and R(Theta) = Identity(2)

scalar FirstPiMatrixElement = 18
scalar noPiParameters = 2

mat b = e(b)
mat V = e(V)
mat Theta = b[1,FirstPiMatrixElement...]'
mat RTheta = I(noPiParameters)
mat VarTheta = V[FirstPiMatrixElement...,FirstPiMatrixElement...]
mat WaldStat = Theta' * inv( RTheta * VarTheta * RTheta' ) * Theta
scalar WaldStatScalar = WaldStat[1,1]
scalar pValue = chi2tail(noPiParameters,WaldStatScalar)


scalar list WaldStatScalar

scalar list pValue


******************************************************************
* Computing the implied estimates of the parameters for the compromise effect c_i
* as a function of the row i in which a choise appears.

cap drop _all
set obs 7

gen row = _n
gen rowContextEffect = .
gen rowContextEffectSD = .
gen rowContextEffectCIlow = .
gen rowContextEffectCIhigh = .

forval row = 1/7 {

        * If "_b[/pi1]" and "_b[/pi2]" do not retrieve the MLE estimates, re-run ml maximize using the coeflegend option
(see line 159 above)
        * Then use the proper notation to retrieve the MLE estimates below
        nlcom (-4*_b[/pi1] - 20*_b[/pi2]) + _b[/pi1] * `row' + _b[/pi2] * `row'^2
        *****
        mat bTemp = r(b)
        mat VTemp = r(V)

        replace row = `row' if row == `row'
        replace rowContextEffect = bTemp[1,1] if row == `row'
        replace rowContextEffectSD = sqrt( VTemp[1,1] ) if row == `row'
        replace rowContextEffectCIlow = rowContextEffect - 1.96 * sqrt( VTemp[1,1] ) if row == `row'
        replace rowContextEffectCIhigh = rowContextEffect + 1.96 * sqrt( VTemp[1,1] ) if row == `row'
}

list


******************************************************************


timer off 1
timer list 1



cap log close


* End of do file
```

12 Original Instructions of the Experiment

Informed Consent

Please consider this information carefully before deciding whether to participate in this research.

Purpose of the research:

The purpose of this study is to examine individual decision-making in an experimental context.

What you will do in this research:

You will sit in front of a computer and be shown a series of questions regarding different monetary scenarios. Your task is simply to indicate which outcome you prefer. If you complete the study, you will have a chance to earn an additional payment (as described below under "Compensation").

Time required:

Participation will take approximately 30 to 45 minutes to complete.

Risks:

There are no anticipated risks associated with participating in this study. The effects of participating should be comparable to those you would experience from viewing a computer monitor for 30 to 45 minutes and using a mouse or keyboard.

Benefits:

At the end of the study, we will provide an explanation of the study and of our hypotheses. We will describe the potential implications of the results of the study both if our hypotheses are supported and if they are disconfirmed. If you wish, you can send an email message to Jonathan Beauchamp (jpbeauch@fas.harvard.edu) or to Brendan Price (priceb@nber.org) and we will send you a copy of any manuscripts based on the research (or summaries of our results).

Compensation:

You will receive a participation fee of $15 for completing the study. If you withdraw from the study without completing it, your participation fee will be decreased as follows:

- You will receive $15 if you finish all four parts (A, B, C, and D).
- You will receive only $11 if you finish only Parts A, B, and C.
- You will receive only $9 if you finish only Parts A and B.
- You will receive only $7 if you finish only Part A.

- You will receive only $5 if you finish none of the four parts of the study.

If you finish all four parts of the study, you will also have have a chance to earn an additional amount of money. At the end of the study, the computer will randomly choose a number from 1 to 6. If it chooses a 6 (a one in six chance), one question from the first part of the study will be selected at random and you may receive an additional payment of no more than $400 on the basis of your answer to that question. Depending on your choices, you may be paid in the form of a monetary gamble giving you a chance of gaining some amount of money and a chance of gaining no additional money.

Although some questions will concern possible monetary losses, you will *not* lose any money as a result of participating in this study.

If you do not finish all four parts, you will not have an opportunity to earn an additional amount of money.

You will be paid by check. In order to receive your payment, you must have listed your current mailing address on your CLER profile so we can mail you your check. Your check will be put in the mail no later than Friday, April 16.

Confidentiality:

Any information that is obtained in connection with this study and that can be identified with you will remain confidential. Your identity will not be stored with your data, and we will not collect your IP address. Your responses will be assigned a code number, and the list connecting your name with this number will be kept in a locked room and will be destroyed once all the data have been collected and analyzed. The data will be kept anonymously for future analysis.

Participation and withdrawal:

Your participation in this study is completely voluntary, and you may withdraw at any time by leaving the study website (no questions will be asked). If you choose to be in this study, you may subsequently withdraw from it at any time. If you withdraw during the course of the study, your participation fee will be determined as described above under "Compensation."

Contact:

If you have questions about this research, please contact Jonathan Beauchamp (jpbeauch@fas.harvard.edu) or Brendan Price (priceb@nber.org). You may also contact the faculty member supervising this work: David Laibson (dlaibson@harvard.edu).

Whom to contact about your rights in this research, for questions, concerns, suggestions, or complaints that are not being addressed by the researcher, or research-related harm:

Jane Calhoun, Harvard University Committee on the Use of Human Subjects in Research, 1414 Mass Ave., 2nd Floor, Cambridge, MA 02138. Phone: 617-495-5459. E-mail: jcalhoun@fas.harvard.edu

---

Agreement:

The nature and purpose of this research have been sufficiently explained and I agree to participate in this study. I understand that I am free to withdraw at any time without incurring any penalty.

Part A: Instructions

In this part, you will make choices about 28 monetary scenarios. For example, a scenario might be:

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

After each scenario is presented, you will be asked to indicate if you would prefer to take the gamble or to gain a fixed amount of money for sure. For example, you might be asked:

Would you rather...

◯Take the gamble OR ◯Gain $80.50

If this were an actual question, you would answer it by clicking on one of the two circles. You will be asked a series of such questions for each scenario. You will not be able to change your answers once you have submitted them.

At the end of the experiment, the computer will randomly choose a number from 1 to 6. If it chooses 6 (a one in six chance), <u>one question</u> will be selected at random and you will be paid on the basis of your answer for that question. For example, if 6 were chosen and the above example question were picked, then depending on which circle you clicked, you would be paid either $80.50 or the result of taking the gamble. (The result of taking the gamble would be determined randomly by the computer in accordance with the indicated percent chances.) We know some of the money amounts are large; however, if a large amount is selected to be paid, we *will* pay you that amount of money.

Because the computer might choose 6, and because each of the following decision-making questions has a chance of being selected, you should answer each question as though that question determined your payment. It also helps us in our research if you answer all the questions as truthfully as you can.

There are no right or wrong answers here. Which choice you make is a matter of personal preference. Please pay careful attention to the amounts in each question and answer according to your own preferences.

Part B: Instructions

In this part, you will again make choices about 28 monetary scenarios. For example, a scenario might be:

A gamble gives you a 75% chance of losing $40 and a 25% chance of losing $20 instead.

After each scenario is presented, you will be asked to indicate if you would prefer to take the gamble or to lose a fixed amount of money for sure. For example, you might be asked:

Would you rather...

○ Take the gamble OR ○ Lose $30.70

If this were an actual question, you would answer it by clicking on one of the two circles. You will be asked a series of such questions for each scenario. You will not be able to change your answers once you have submitted them.

The questions in this part are hypothetical only -- although they concern possible monetary losses, you will not be paid or have to pay any money to us for your answers in this part. Nonetheless, we ask you to answer all the questions as truthfully as you can, as if they were associated with real monetary outcomes.

There are no right and wrong answers here. Which choice you make is a matter of personal preference. Please pay careful attention to the amounts in each question and answer according to your own preferences.

Part C: Instructions

In this part, you will make choices about four monetary scenarios. Each scenario will describe a gamble giving you a 50% chance of losing some amount of money and a 50% chance of instead gaining some amount of money that changes from question to question. For example, a scenario might begin:

A gamble gives you a 50% chance of losing $80 and ...

A question might then complete the scenario with:

... a 50% chance of gaining $120.50 instead.

For each question, you will be asked to indicate whether you would prefer to take the gamble or not to take the gamble:

Would you rather ...

○Take the gamble OR ○Not take the gamble

If this were an actual question, you would answer it by clicking on one of the two circles. You will be asked a series of such questions for each scenario. You will not be able to change your answers once you have submitted them.

The questions in this task are hypothetical only -- although they concern possible monetary losses, you will not be paid or have to pay any money to us for your answers in this part. Nonetheless, we ask you to answer all the questions as truthfully as you can, as if they were associated with real monetary outcomes.

There are no right and wrong answers here. Which choice you make is a matter of personal preference. Please pay careful attention to the amounts in each question and answer according to your own preferences.

Part D: Instructions

In this part, you will make choices about four monetary scenarios. Within each scenario, "gamble 1" will stay the same but "gamble 2" will change from question to question. For example, the scenario might begin:

Gamble 1 gives you a 50% chance of losing $60 and a 50% chance of gaining $200 instead.

A description of Gamble 2 might begin:

Gamble 2 gives you a 50% chance of losing $100 and ...

A question might then complete the description of Gamble 2 with:

... a 50% chance of gaining $300.10 instead.

For each question, you will be asked to indicate whether you would prefer to take Gamble 1 or to take Gamble 2, as completed by the question:

Would you rather ...

○Take gamble 1 OR ○Take gamble 2

If this were an actual question, you would answer it by clicking on one of the two circles. You will be asked a series of such questions for each scenario. You will not be able to change your answers once you have submitted them.

The questions in this task are hypothetical only -- you will not be paid or have to pay any money to us for your answers. Nonetheless, we ask you to answer all the questions as truthfully as you can, as if they were associated with real monetary outcomes.

There are no right and wrong answers here. Which choice you make is a matter of personal preference. Please pay careful attention to the amounts in each question and answer according to your own preferences.

Debrief

This experiment was conducted to explore people's attitudes towards gains and losses. Prior research suggests that people dislike financial risks and are more sensitive to potential losses than to potential gains. Economic theory provides methods of measuring risk and loss attitudes on the basis of choices about monetary gambles. However, decisions in laboratory experiments are often influenced by seemingly irrelevant factors. A main purpose of our study is to determine whether people's willingness to take monetary gambles is affected by the wording and ordering of the questions we ask.

This concludes your participation in our study. Thank you for participating! We will mail your payment to the mailing address listed on your CLER profile. We will put your check in the mail no later than Friday, April 16. Please contact the study administrator at laibson.study@gmail.com if you have any questions.

13 References

See the main text's References section (all works cited in this Online Appendix are also cited in the main text).