Controlling for the Compromise Effect Debiases Estimates of Risk Preference Parameters*

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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

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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 adults 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.[1]

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.[2] 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., Holt and Laury 2002, Harrison, List, and Towe 2007, Andersen, Harrison, Lau, and Rutström 2008)[3] 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).[4]

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

[1] Throughout, we assume that stable, "deep" preferences exist. An alternative (psychological) tradition views preferences as "constructed" and inherently unstable from one choice to the next (e.g., Slovic, 1995).

[2] Our approach follows a long tradition of modeling multiple mechanisms simultaneously, because the omission of one mechanism biases the estimation of the other mechanisms (omitted variable bias).

[3] We are not taking sides in the debate about the external validity of MPL procedures. Instead, we are showing how our method improves internal validity. Other procedures (e.g., the convex time budget for eliciting time preferences; Andreoni and Sprenger, 2012) that might similarly be affected by the compromise effect could also benefit from application of our method.

[4] We use the term compromise effect as short-hand for a bias toward the middle option, which is what these papers document.

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 (e), although rows (a) and (f) 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).[5] 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 no loss aversion.

Third, when we estimate the prospect-theory parameters while including additional structural parameters to capture the compromise effect, our estimates of γ and λ are robust across the five

[5] 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.

scale treatment conditions. (When estimating the model pooling all of our experimental data, our estimates are $\hat{\gamma} = 0.24$ and $\hat{\lambda} = 1.31$, which falls within the range of estimates in the existing literature, albeit with $\hat{\lambda}$ toward the lower end of the range.) The robustness of these preference-parameter estimates implies that they are not biased by the compromise effect.

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.[6]

A limitation of our experiment is that only one out of its four parts (i.e., sets of questions) 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. Section 8 discusses the results of our expected value manipulation. Section 9 concludes.

2 Experiment

2.1 Design

Throughout the experiment, we employ the Multiple Price List (MPL) elicitation method (Holt and Laury, 2002).[7] At the top of each computer screen, a *fixed prospect* is presented. The fixed

[6] 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 (vs. one or two in our experiment).

[7] While our procedure is a Multiple Price List according to conventional usage of the term, it is not the same as Holt and Laury's (2002) procedure. Holt and Laury offer their participants choices between gambles that vary in the probability of the good outcome. In contrast, as illustrated by the screenshots in the Introduction, our alternatives

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.[8] 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.[9]

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

are sure-things (not gambles). Accordingly, across the rows we vary the value of the sure-thing alternative.

[8] 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. An auto-fill feature of the computer program fills in the other circles. This procedure is a version of the "Switching MPL" (or "sMPL") design discussed by Andersen et al. (2006), in which participants are asked to choose at which row they want to switch.

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

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).[10] Because the range of estimates of γ in the literature falls well within this interval (Booij, van Praag, and Kullen, 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.[11] 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%

[10] We use $\gamma = 0.99$, rather than $\gamma = 1$, to generate our lowest alternative outcomes because $\gamma = 1$ corresponds to log utility and implies a certainty equivalent of \$0 for any prospect with a chance of a \$0 outcome, regardless of how small the probability of that \$0 outcome is.

[11] K&T designed Parts C and D primarily to measure loss aversion.

chance of a loss and 50% chance of a gain. For example, one of the screens in Part C is:

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

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

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

Part D also comprises four screens, each containing choices between a fixed 50%-50% risky prospect and seven alternative 50%-50% risky prospects. On two of the four screens, both the fixed 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.[12] 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

[12] K&T designed these two screens as placebo tests for loss aversion; we therefore do not use the data from these screens in our estimation.

$\lambda = 3$ 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).

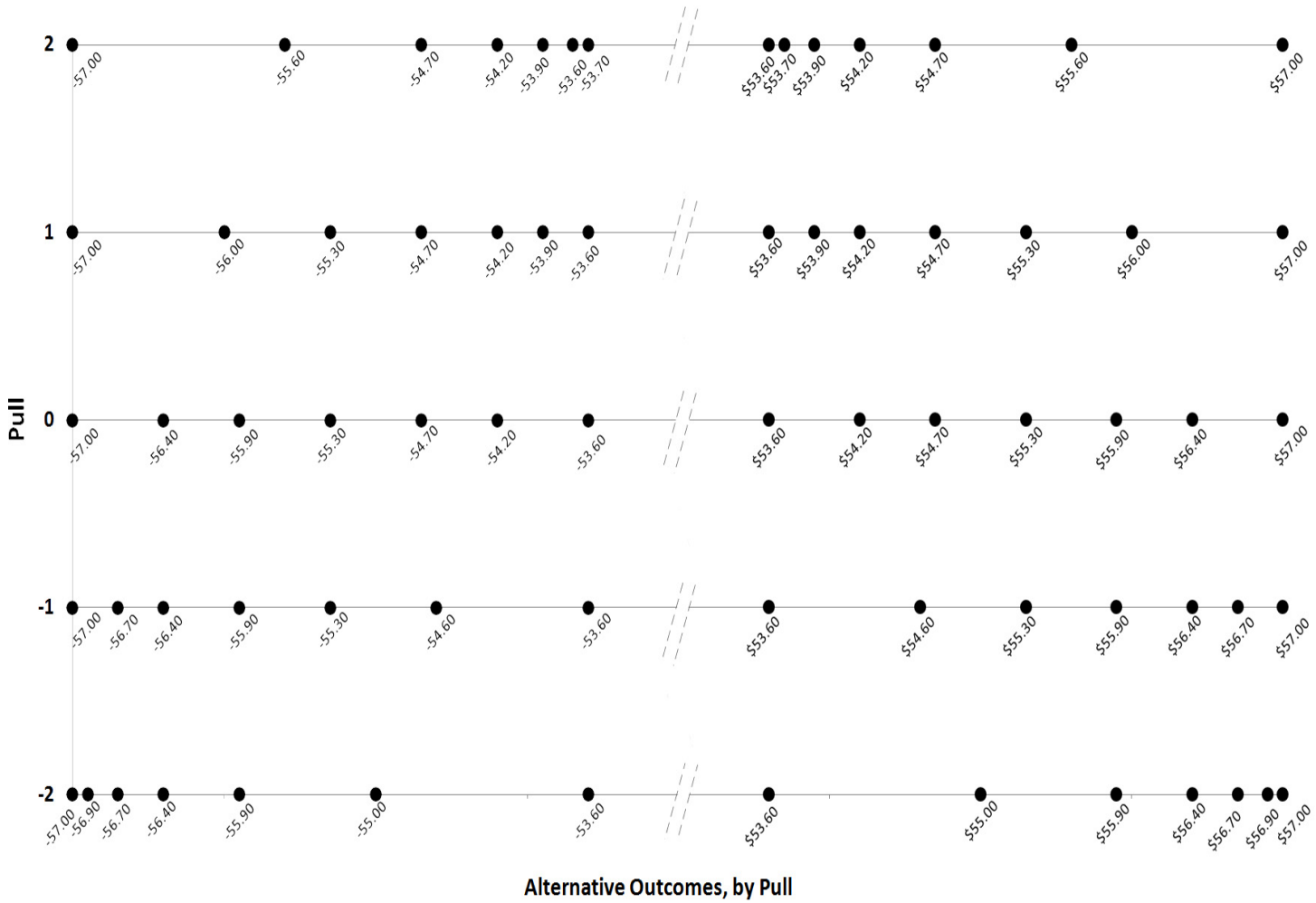

FIGURE 1. Alternative outcomes by Pull treatment for example screens. The right side of the figure shows alternative outcomes by Pull treatment for an example screen from Part A with a fixed prospect offering a 10% chance of gaining \$100 and a 90% chance of gaining \$50. The left side of the figure 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. They are mainly recruited through flyer postings around neighboring campuses.

At the launch of the experiment, the CLER lab posted a description to advertise the experiment to the members of the online subject pool database. Any member of the pool could then participate until a sample size of 550 was reached. Each participant was pseudo-randomly assigned to one Pull and to one EV treatment to ensure that our treatments were well-balanced. A total of 521 participants completed all four parts of the experiment. The mean response time for the participants who completed the experiment in less than one hour was 32 minutes.[13]

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

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

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., Trepel, Fox, and Poldrack, 2005; 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.[14]

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}.[15] Following Hey and Orme (1994), we use a Fechner

[14] As a robustness check, we estimated the model with T&K's probability weighting function (with the data from all parts of the experiment): $\omega(p) = p^{\alpha}/(p^{\alpha} + (1-p)^{\alpha})^{\frac{1}{\alpha}}$. The results presented below are robust to the use of this alternative function (see the Online Appendix for details).

[15] In Part C, the alternative prospects are presented in increasing order of monetary payoff. We ignore this subtlety here for expositional purposes.

error specification and assume that on any screen q, the participant chooses P_{qi} over P_{qf} if and only if

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

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_{qA}, and ε_q are preference shocks that vary across (but not within) screens. We assume that $\varepsilon_{qf} - \varepsilon_{qA} \equiv \varepsilon_q \sim N(0,1)$. We refer to c_i as the *parameter for the compromise effect of row* i,[16] and we assume that $\Sigma_{i=1}^{7} c_i = 0$.[17]

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 $\gamma < 1$.[18] 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.[19] Second, we assume that c_i takes the quadratic functional form $c_i = \pi_0 + \pi_1 \cdot i + \pi_2 \cdot i^2$.[20] With this functional form, the

[16] As mentioned above, we view the compromise effect as biasing the expression of the participants' deep CPT preferences. Accordingly, we view the c_i parameters as nuisance parameters.

[17] This assumption implies that the parameters for the compromise effect do not on average bias participants towards selecting either the alternative or the fixed prospect across the rows of a screen.

[18] Fifteen of the 28 fixed prospects in Part A have a chance of yielding \$0 (and likewise for Part B). $\gamma \geq 1$ would imply extremely risk-averse behavior with these 15 prospects, such that any positive alternative sure outcome would always be preferred with probability 1. Every participant in the experiment made choices ruling out such extreme risk aversion, except for one participant. That participant picked the alternative sure outcome in every single choice in Part A. (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.)

[19] More precisely, 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) for their representative sample. We thus 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 prospects of Part C, respectively, and σ_D for the two prospects of Part D.

We also attempted to estimate the model with a different σ_q parameter for each screen. The results are robust to that specification when the data from Part A only are used. However, we encountered convergence problems when estimating the model with the data from all parts of the experiment (because of the very large number of parameters estimated simultaneously) and with the data from Part B (because the MLE maximization algorithm pushed the σ_q parameter for one of the screens toward infinity).

[20] An alternative would have been to assume a linear specification for c_i, but that would have constrained c_i in the middle row to equal zero—a feature of the results that bears directly on whether participants have a tendency to switch in the middle row, as discussed below. The quadratic specification is more flexible and does not impose this constraint.

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.[21] 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 from participants for whom the MLE algorithm does not converge[22] when the CPT model without parameters for the compromise effect 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 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

[21] 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 can be understood as primarily identifying $\hat{\lambda}$. Data from those two screens are excluded from all estimations. Here and from now on, whenever we refer to "all screens from Parts A-D," we mean all screens excluding these two.

[22] To be precise, we exclude participants for whom the relative change in the coefficient vector from one iteration to the next is still greater than 1×10^{-4} after 500 iterations of the MLE algorithm.

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:[23]

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

The likelihood function for all the participants pooled together is $\Pi_{p\epsilon P} L_p$, where P is the set of participants.

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 column 2 of the MPL), and a negative value of c_i implies a bias in favor of choosing the fixed prospects (which is in column 1 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).[24] For instance, consider the two example screenshots

[23] For notational simplicity, we write $\Pr_{q,0,1}$ for $\Pr_{q,-,1}$ and $\Pr_{q,7,8}$ for $\Pr_{q,7,-}$.

[24] The foregoing is accurate in the context of CRRA preferences with no probability weighting function. However, we estimate CPT preferences, which include a probability weighting function. Nonetheless, we believe that the logic underlying the following hypotheses is robust to the inclusion of reasonable specifications of a probability weighting function in the model.

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 $\hat{\gamma}^+ = 0.448$. These estimates are broadly in line with existing estimates in the literature, although the estimate of γ^- is below what is typically found.[25] Indeed, 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, on the lower end of the range of loss aversion estimates in the literature.[26] The estimates of the probability weighting function parameters, $\hat{\alpha}$ and $\hat{\beta}$, are broadly in accord with findings from prior work.[27]

<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

[25] Booij, van Praag, and Kullen's (2010) Table 1 reviews existing experimental estimates. Translated into the CRRA functional form we estimate, the range of existing parameter estimates is $\hat{\gamma}^+ \in [-0.01, .0.78]$ in the gain domain and $\hat{\gamma}^- \in [-0.06, 0.39]$ in the loss domain.

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

[27] Our estimates of α range from 0.564 to 0.690 and our estimates of β range from 0.858 to 1.471. Booij, van Praag, and Kuilen's (2010) Table 1 only lists three studies that estimated the two-parameter Prelec (1998) functional form, and they only did so for prospects in the gain domain. The ranges of estimates are $\hat{\alpha}^+ \in [0.53, 1.05]$ and $\hat{\beta}^+ \in [1.08, 2.12]$. Hence, our $\hat{\beta}^+$ estimate (obtained from the data from Part A only) falls below the lower end of the range.

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.[28]

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, and their standard errors and confidence intervals are calculated using the delta method. 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 significant: 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.

[28] Wakker (2010, section 9.6) highlights two serious concerns with assuming different parameters in the gain and loss domains if $u^+(x) = \frac{x^{1-\gamma^+}}{1-\gamma^+}$ and $u^-(x) = \frac{x^{1-\gamma^-}}{1-\gamma^-}$ 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 can make estimates of λ especially sensitive to exactly which prospects are used in the experiment.

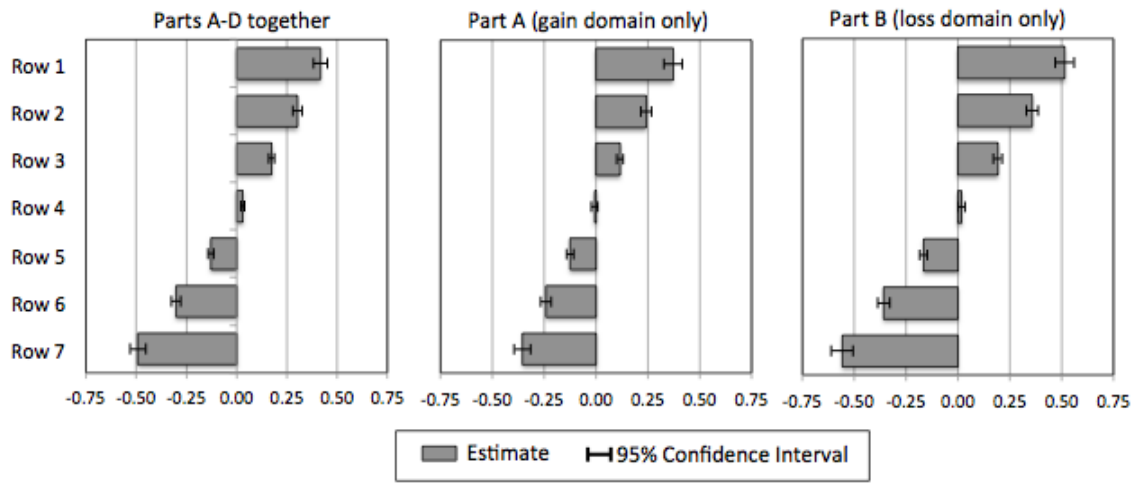

FIGURE 2. Implied estimates of the parameters for the compromise effect c_i as a function of the row i in which a choice appears. The standard errors and confidence intervals are obtained with the delta method. In the estimation, we parameterize the parameters for the compromise effect with the quadratic 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, by the delta method, $var(\hat{c}_i) \approx (i-4)^2 var(\hat{\pi}_1) + (i^2-20)^2 var(\hat{\pi}_2)$ (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.[29] Figure 3 shows estimates of γ, γ^+ and γ^-, with 95% confidence intervals, for each subsample. Figure 4 shows estimates of λ.

[29] Though this may not at first be obvious, the parameters for the compromise effect are identified in these subsamples because the tendency to switch toward the middle row of the MPL is a feature of the data that is distinguishable from CPT preferences, even within each subsample.

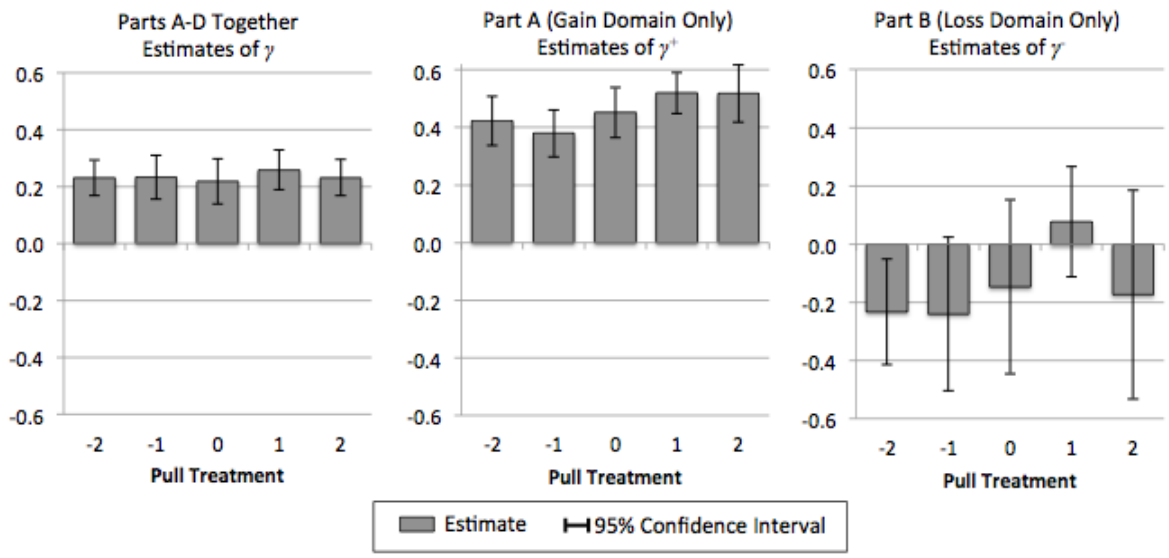

FIGURE 3. Estimates of γ, γ^+, and γ^- by Pull treatment, from the model with the compromise effect. The negative estimates of γ^- for Part B reflect risk aversion in the loss domain, unlike what CPT predicts. (γ is not estimated for Parts C and D only because these parts have few questions.)

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.[30]

[30] As can be seen from Figures 5 and 6 below, which present estimates of γ, γ^+, γ^-, and λ by Pull treatment from the model without the compromise effect, a linear specification for the Pull variable is a reasonable approximation.

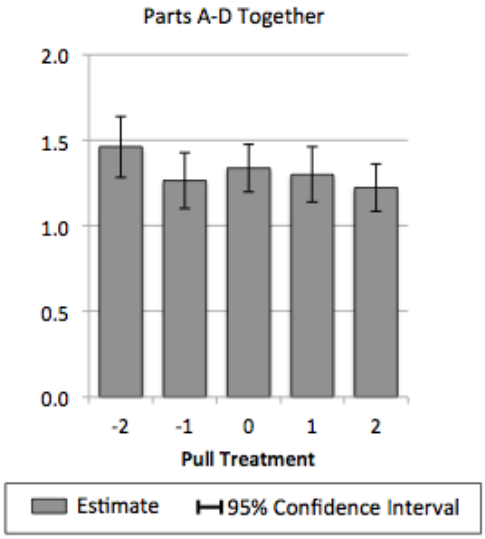

FIGURE 4. Estimates of λ by Pull treatment from the model with the compromise effect, for Parts A-D together. (λ cannot be estimated for Part A only or Part B only because the questions in these parts are all in the gain or loss domains. We do not estimate λ for Parts C and D only because these parts 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. In contrast, 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.[31]

<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.

[31] We note that the parameter estimates in Tables 1 and 3 are in fact not too dissimilar, but we believe this similarity is coincidental and this would not be the case had we used different Pull treatments in the experiment.

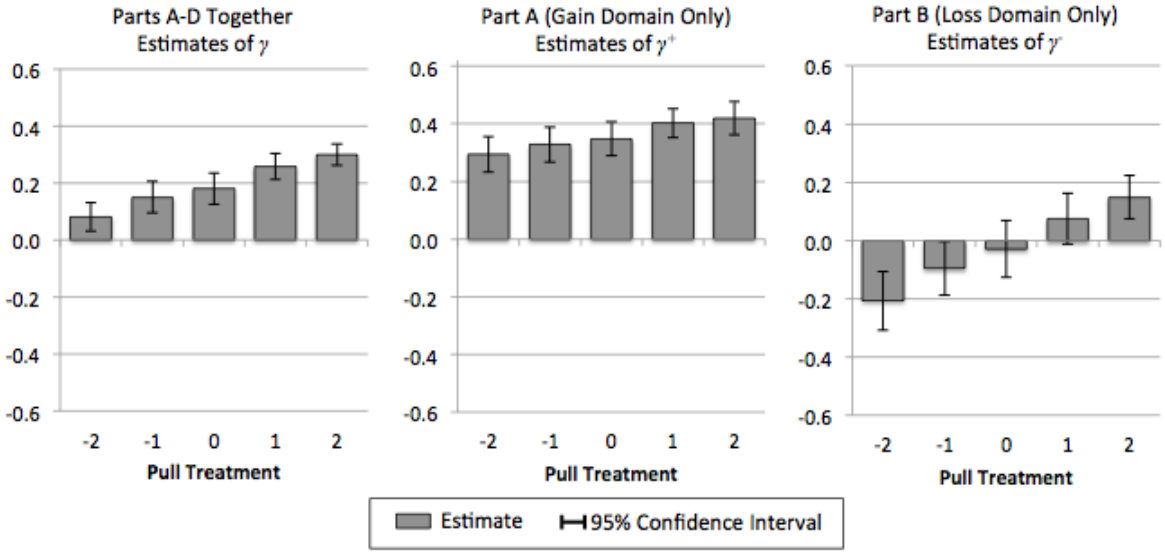

FIGURE 5. Estimates of γ, γ^+, and γ^- by Pull treatment, from the model without the compromise effect. This figure is analogous to Figure 3, except that the estimated model does not control for the compromise effect.

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 γ, 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).

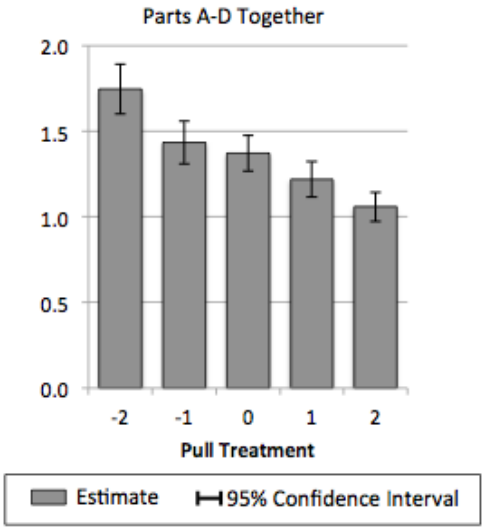

FIGURE 6. Estimates of λ by Pull treatment from the model without the compromise effect, for Parts A-D together. This figure is analogous to Figure 4, except that the estimated model does not control for the compromise effect.

<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 (as defined in Section 3.2) the parameter σ_q regulates the relative importance of utility vs. the other arguments (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

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

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.[32]

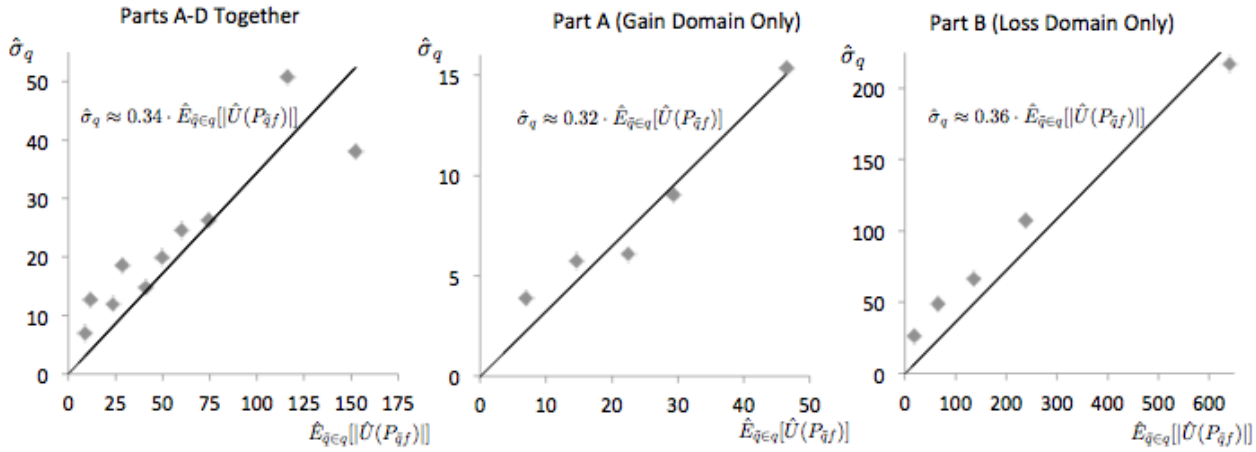

FIGURE 7. Relationship between $\hat{\sigma}_q$ and the expected utility of a screen's fixed prospect. See text for details.

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.

[32] 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 significantly larger than 0 but relatively small for all three sets of estimation results. For the estimates of $\hat{\Delta}$ that we report here, we set the intercept equal to 0.

8 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) and make their preferences more risk neutral.[33] 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 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. As discussed in the introduction, a key 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.

9 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.

As in T&K, our estimation of the prospect-theory parameters has assumed that the reference

[33] Furthermore, to the extent that risk aversion over small-stakes prospects and loss aversion are due to cognitive errors in comprehending the value of a prospect, displaying information that is useful for assessing a prospect's value—such as its expected value—may decrease small-stakes risk aversion and loss aversion. Motivated by that hypothesis, Benjamin, Brown, and Shapiro (2013) examined a similar manipulation.

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.[34]

Our analysis also raises the question of why loss aversion estimates vary across published studies. Wakker (2010, p.265) concludes that "loss aversion is volatile and depends much on framing, and [Tversky and Kahneman's (1992) loss aversion estimate] $\lambda = 2.25$ cannot have the status of a universal constant." Estimates of loss aversion range from 0.74 to 8.27 in one pair of reviews: Booij, van Praag, and Kullenís (2010, Table 1) and Abdellaoui, Bleichrodt, and Paraschiv (2007, Tables 1 and 5). Identifying the aspects of this variation that can be explained by the compromise effect (and perhaps other context effects) constitutes a promising future research program.

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. However, the methodology we demonstrate—jointly estimating the compromise effect and preference parameters—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

[34] One simple but extreme possibility that has been explored (Sprenger, 2015) is that the fixed prospect in the current choice problem's price list pins down a participant's expectation. We note that since the fixed prospect was held constant across our scale manipulations, the scale effects we find could not be explained by a version of prospect theory with this model of reference point formation.

Song (2015) examines a natural implementation of the reference-point-as-expectations model in an experiment in which participants experience a binary gamble before facing a single Multiple Price List. He finds evidence that the reference point is determined partially by expectations set by the earlier gamble. This evidence, however, does not bear on whether the reference-point-as-expectations theory could also explain the compromise effect that we explore.

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, or 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 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).

10 REFERENCES

Abdellaoui, Mohammed, Han Bleichrodt, and Corina Paraschiv. 2007. "Loss Aversion Under Prospect Theory: A Parameter-Free Measurement." *Management Science*, 53(10): 1659–1674.

Andersen, Steffen, Glenn W. Harrison, Morten I. Lau, and Elisabet E. Rutström. 2006. "Elicitation Using Multiple Price List Formats." *Experimental Economics*, 9(4): 383–405.

Andersen, Steffen, Glenn W. Harrison, Morten I. Lau, and Elisabet E. Rutström. 2008. "Eliciting Risk and Time Preferences." *Econometrica*, 76(3): 583–618.

Andreoni, James, and Charles Sprenger. 2012. "Estimating Time Preferences from Convex Budgets." *American Economic Review*, 102(7): 3333-3356.

Benjamin, Daniel J., Sebastian A. Brown, and Jesse M. Shaprio. 2013. "Who is 'Behavioral'? Cognitive Ability and Anomalous Preferences." *Journal of the European Economic Association*, 11(6): 1231-1255.

Birnbaum, Michael H. 1992. "Violations of Monotonicity and Contextual Effects in Choice-Based Certainty Equivalents." *Psychological Science*, 3(5): 310–314.

Booij, Adam S., Bernard M.S. van Praag, and Gijs van den Kullen. 2010. "A parametric analysis of prospect theory's functionals for the general population." *Theory and Decision*, 68: 115–148.

Bruhin, Adrian, Helga Fehr-Duda, and Thomas Epper. 2010. "Risk and Rationality: Uncovering Heterogeneity in Probability Distortion." *Econometrica*, 78(4): 1375–1412.

Choi, Syngjoo, Raymond Fisman, Douglas Gale, and Shachar Kariv. 2007. "Consistency and Heterogeneity of Individual Behavior under Uncertainty." *American Economic Review*, 97(5): 1921-1938.

Fehr-Duda, Helga and Thomas Epper. 2012. "Probability and Risk: Foundations and Economic Implications of Probability-Dependent Risk Preferences." *Annual Review of Economics*, 4:567-593.

Harrison, Glenn W., Morten I. Lau, Elisabet E. Rutström, and Melonie B. Sullivan. 2005. "Eliciting Risk and Time Preferences Using Field Experiments: Some Methodological Issues." In *Field experiments in economics (Research in Experimental Economics, Volume 10)*, ed. J.

Carpenter, G. Harrison, and J. List, 125–218. Emerald Group Publishing Limited.

Harrison, Glenn W., Morten I. Lau, and Elisabet E. Rutström. 2007. "Estimating Risk Attitudes in Denmark: a Field Experiment." *Scandinavian Journal of Economics*, 109(2): 341–368.

Harrison, Glenn W., John A. List, and Charles Towe. 2007. "Naturally Occurring Preferences and Exogenous Laboratory Experiments: A Case Study of Risk Aversion." *Econometrica*, 75(2): 433–458.

Harrison, Glenn W. and Elisabet E. Rutström. 2008. "Risk Aversion in the Laboratory." In *Risk Aversion in Experiments (Research in Experimental Economics, Volume 12)*, ed. J. Cox, G. Harrison, 41–196. Emerald Group Publishing Limited.

Hey, John D., and Chris Orme. 1994. "Investigating Generalizations of Expected Utility Theory Using Experimental Data." *Econometrica*, 62(6): 1291-1326.

Holt, Charles A., and Susan K. Laury. 2002. "Risk Aversion and Incentive Effects." *American Economic Review*, 92(5); 1644–1655.

Kahneman, Daniel, and Amos Tversky. 1979. "Prospect Theory: An Analysis of Decision Under Risk." *Econometrica*, 47(2): 263–291.

Kamenica, Emir. 2008. "Contextual Inference in Markets: On the Informational Content of Product Lines." *American Economic Review*, 98(5): 2127–2149.

Koppell, Jonathan G. S., and Jennifer A. Steen. 2004. "The Effects of Ballot Position on Election Outcomes." *Journal of Politics*, 66(1): 267-281.

Köszegi, Botond, and Matthew Rabin. 2006. "A Model of Reference-Dependent Preferences." *Quarterly Journal of Economics*, 121(4): 1133-1165.

Köszegi, Botond, and Matthew Rabin. 2007. "Reference-Dependent Risk Attitudes." *American Economic Review*, 97(4): 1047-1073.

Lichtenstein, Sara, Paul Slovic, and Donald Zink. 1969. "The Effect of Instruction in Expected Value Optimality of Gambling Decisions." *Journal of Experimental Psychology*, 79(2): 236–240.

Montgomery, Henry, and Thomas Adelbratt. 1982. "Gambling Decisions and Information About Expected Value." *Organizational Behavior and Human Performance*, 29: 39–57.

Prelec, Drazen. 1998. "The Probability Weighting Function." *Econometrica*, 66(3): 497–527.

Simonson, Itamar. 1989. "Choice Based on Reasons: The Case of Attraction and Compromise

Effects." *Journal of Consumer Research*, 16(2): 158-174.

Slovic, Paul. 1995. "The Construction of Preference." *American Psychologist*, 50(5): 364-371.

Song, Changcheng. 2015. "An Experiment on Reference Points and Expectations." Working Paper.

Sprenger, Charles. 2015. "An Endowment Effect for Risk: Experimental Tests of Stochastic Reference Points." *Journal of Political Economy*, 123(6): 1456-1499.

Trepel, Christopher, Craig R. Fox, and Russel A. Poldrack. 2005. "Prospect Theory on the Brain? Toward a Cognitive Neuroscience of Decision Under Risk." *Cognitive Brain Research*, 23(1): 34–50.

Tversky, Amos, and Daniel Kahneman. 1974. "Judgment under Uncertainty: Heuristics and Biases." *Science*, 185(4157): 1124–1131.

Tversky, Amos, and Daniel Kahneman. 1992. "Advances in Prospect Theory: Cumulative Representation of Uncertainty." *Journal of Risk and uncertainty*, 5(4): 297–323.

Wakker, Peter P. 2010. *Prospect Theory: For Risk and Ambiguity.* Cambridge University Press, Cambridge, UK.

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.

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^-		0.556***	0.505***	0.617***
		(0.019)	(0.018)	(0.027)
β, β^+, β^-		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.

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.

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^-		0.535***	0.497***	0.577***
		(0.012)	(0.014)	(0.016)
β, β^+, β^-		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.

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.

11 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