The Effects of Frame and Partisan Bias on Risky-Choice

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Abstract

In typical experiments examining the role of gain-loss framing on risky-choice, great care is taken to ensure that the scenarios are generic enough to avoid outside sources of bias. However, policy proposals in the real world that can have significant effects on human lives or involve large sums of money often originate from a partisan source. I examine the extent to which partisan identity influences choice in a standard risky-choice framing paradigm. I also test dual-process theory predictions for how the conflict between partisan loyalty and frame should reduce framing bias (but not partisan bias). Participants were given 12 hypothetical framing problems (6 gain/6 loss) in which the U.S. Congress was entertaining two policy proposals (sure/risky) in each scenario. In 8 of the problems, I manipulated which political party (Republican/Democrat) proposed which option. In the remaining 4, both options are bipartisan (Plan A/Plan B). I also measured participants' partisan identity. Consistent with standard framing, participants were more risk-averse when options were framed as gains and more risk seeking when framed as losses. However, independent of the effect of frame, decision-makers' risk-preferences also shifted in favor of their preferred party's proposal. Data, syntax, and preregistration can be found at <https://osf.io/gcbez/>.

Keywords: Risky-Choice, Framing, Partisan Bias, Dual-process Theory

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Elected officials are tasked with proposing and enacting solutions to public policy problems, some of which involve putting large amounts of money or human lives at risk. One factor that determines whether policy is enacted is the level of support coming from voters. Whereas the ideal voter would approach policies by objectively weighing the risks and benefits of each option, research in judgment and decision making has shown that individuals are susceptible to a number of biases when it comes to decisions involving risk (Kahneman, 2011). One such bias – the risky-choice framing effect – occurs when individuals shift their risk preferences depending on whether the same decision is framed in terms of gains or losses. The classic demonstration of this bias involves a public policy decision in which 600 lives are at risk from a deadly disease and decision-makers must to choose between two options – a safe option (Program A: Gain: 200 people saved; Loss: 400 people die) and a risky option (Program B: Gain: 1/3 chance 600 people saved, 2/3 chance nobody saved; Loss: 2/3 chance 600 people die, 1/3 chance nobody dies). When framed as gains, decision-makers tend to prefer the safe option (Program A) on average, however when the identical problem is framed in terms of losses, the average preference flips in favor of the risky option (Program B) (Tversky & Kahneman, 1981).

Originally, each proposal in the disease problem was largely stripped of context as to avoid confounding the effect of frame. However, outside of the laboratory, public policy proposals must come from somewhere. Although it may seem like the source of a proposal should not matter when outcomes (risks and rewards) are clearly described, a large amount of work on partisan bias suggests

otherwise – particularly when the source is political (Ditto et al., 2018; Kahan, 2015; Van Bavel & Pereira, 2018). In this paper, I test how both framing and partisan identity (how strongly one identifies with the Republican or Democratic party) influence risky-choice when proposals for dealing with public policy issues are provided by partisan sources.

Standard Dual-process Explanation of Risky-Choice Framing

Standard dual-process theories in judgment and decision making suggest that people rely on either an automatic, associative system (System 1) or a working-memory-intensive, deliberative system (System 2) (I use the term “standard” to denote the fact that there are several dual-process theories that share a number of fundamental commonalities; Evans & Stanovich, 2013). A key challenge in the dual-process literature is to understand the mechanism underlying switches from System 1 (which again, is automatic) to the deliberative System 2 (De Neys & Glumicic, 2008; Epstein, 1994; Kahneman & Frederick, 2002; Pennycook, Fugelsang, & Koehler, 2015; Stanovich & West, 2008).

One account (coined the default-interventionist approach; Kahneman & Frederick, 2002; Stanovich & West, 2008) proposes that System 2 is a lax monitor of System 1. It looks out for inconsistencies in reasoning, and activates when one is detected, but generally requires that the inconsistency be fairly obvious. In this account, the quality of monitoring varies with cognitive abilities/thinking dispositions (e.g., working memory, actively open-minded thinking – called the “algorithmic mind” in Stanovich, 2009). An alternative account (coined the parallel-

competitive approach; De Neys & Glumicic, 2008; Epstein, 1994; Sloman, 1996) suggests that individuals are intuitively aware of inconsistencies resulting from automatic, intuitive responding in reasoning, but generally fail to inhibit this automatic response (indicating a failure of inhibition rather than monitoring.) A more recent account proposes a hybrid of these two approaches, suggesting that individuals can have multiple intuitions (some which are logically coherent and others which are not), and that it is conflicts between these intuitions along with individual differences in one's propensity to strictly monitor one's thinking that cues a switch from System 1 to System 2 processing (Pennycook, Fugelsang, & Koehler, 2015).

Standard dual-process theories assume that framing effects result from from a reliance on intuitive System 1 processes, which compare how each option makes the individual feel (i.e., an emotional response to the positive or negative valence of each option; De Martino, Kumaran, Seymour, & Dolan, 2006; Gosling & Moutier, 2018; Kahneman & Frederick, 2007; McElroy & Dickenson, 2010). System 2 processing can be provoked via the detection of a conflict between frames, as in experiments in which participants receive both gain and loss frames and recognize that they are receiving essentially identical problems with superficial differences in wording (Stanovich & West, 2008; Corbin, Reyna, Weldon, & Brainerd, 2015). Reduced susceptibility is also hypothesized to occur when there is greater emotional distance from the problem, thus activating deliberative processes due to a lack of an emotional cue (Costa, Foucart, Arnon, Aparici, & Apesteguia, 2014; De Martino, Harrison, Knafo, Bird, & Dolan, 2008; Keysar, B., Hayakawa, & An, 2012).

Theoretical Approaches to Partisan Bias

Politically motivated reasoning provides a common explanation for partisan bias – individuals are motivated to interpret information in ways that satisfy the goal of protecting their partisan identity (Kahan, 2015; Kunda, 1990; Leeper & Slothuus, 2014; Peterson, Skov, Serritzlew, & Ramsøy, 2013). In one demonstration of partisan motivated reasoning, Kahan, Peters, Dawson, and Slovic (2017) gave participants a covariation detection task in which participants evaluated whether cities allowing concealed carry for handguns had more or less gun crime than those banning it, based on frequency of increased and decreased crime incidents. The covariation detection task was set up so that comparing numerical magnitudes (comparing number of instances in which crime increased) led one to the incorrect conclusion whereas calculating and comparing probabilities (probability of increase) led to the correct conclusion. When the results conflicted with partisan identity, performance suffered. Furthermore, whereas more numerate participants performed better in a non-politicized scenario (judging effectiveness of a skin-rash cream), more numerate participants were actually more likely to be biased by their partisan identity in the concealed-carry scenario. Thus, in standard dual-process parlance, partisan motivated reasoning can be a function of System 2.

Whereas Kahan et al.'s work focuses on demonstrating instances in which partisan bias stems from System 2 processes, there is also research suggesting that partisan bias can stem from System 1 processing (Taber & Lodge, 2016) and that reliance on System 2 can actually decrease partisan bias in some contexts. For

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example, Pennycook and Rand (2018) had participants rate the reliability of true and false news stories and also gave participants the Cognitive Reflection Test (which served as a proxy for propensity for System 2 processing.) They observed greater ability to distinguish true from false news stories regardless of partisan leaning or which party was favored by the content in those who scored higher on the Cognitive Reflection Test – suggesting that System 2 can be protective against partisan bias.

How Frame and Partisan Bias Influence Risk-Preference

In this experiment, I examine the framing effect for risky-choices in which opposing political parties propose the risky or safe options. The most interesting comparison in this instance occurs when identity encourages a risk preference counter to that of the framing effect. According to standard dual-process theories, pitting the effect of frame (a System 1, emotion-driven process) against partisan identity (which can operate at the level of either intuition or deliberation) should induce a conflict. This conflict should encourage reliance on deliberative, System 2 processing, and thus reduce (or eliminate) the framing effect in favor of choosing the option in line with one's identity.

Alternatively, it is possible that the effects of partisan identity and frame are mutually exclusive. The motivating force of identity may shift risk preferences in favor one one's partisan identity, but do so additively with respect to frame instead of interactively, leaving the framing effect intact. This result would not support a model by which conflict between intuitions (the desire for partisan loyalty versus

the affective response to frames) engages a System 2 process to yield an unbiased assessment of the outcomes.

Method

Participants

Two hundred participants were recruited from Mechanical Turk. My preregistration stated that I would start with 200 participants, and if analyses warranted more participants, I would collect more. Results demonstrated that 200 participants were sufficient for the preregistered analyses. All data, syntax and the preregistration for analyses can be found at <https://osf.io/fx4c6/>. Mturkers were paid \$0.60 for their participation (and had a median completion time of 4 minutes.) The sample was 57% male, 82% White, 8% African American, 5.5% Asian, 2% American Indian/Alaskan Native, 0.5% Native Hawaiian/Pacific Islander, and 2% preferred not to answer; 88% were Non-Hispanic or Latino, 9.7% were Hispanic or Latino, and 2.5% preferred not to answer. The average age of the sample was 35.01 years ($SD = 11.01$, min = 19, max = 69).

Materials

Twelve risky-choice framing scenarios were developed – all scenarios involved a national issue in which Congress had proposed two policy responses. Half of the scenarios involved monetary gains or losses (e.g., The auto-industry in the United States is in a financial crisis, and the government has decided to invest \$180 million to bail it out.) and the other half involved lives at risk (e.g., Congress is preparing for a cyber attack on our cities' electrical grids, which could end up killing

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an estimated 3,000 people.) In every problem, choosing the sure option would yield a sure gain of 1/3 of the total lives/money at risk or a sure loss of 2/3 of the lives/money at risk (depending on the frame.) The risky option involved a 1/3 chance of saving all of - and 2/3 chance of saving none of - the total lives/money at risk or a 2/3 chance of losing all of - and 1/3 chance of losing none of - the total lives/money at risk. The endowments varied by individual scenario, but scenarios involving money had systematically larger endowments to maintain realism (see Supplemental Materials for exact scenarios). In four of the scenarios, Republicans supported the safe option whereas Democrats supported the risky option, in four of the scenarios the reverse was true, and in the final four scenarios, participants were told that both solutions were bipartisan and were labeled “Plan A” and “Plan B” (as opposed to “Republican Plan” and “Democrat Plan”.) Frame (gain, loss) and Party support (Republican safe, Democrat safe, Bipartisan) were randomly assigned to scenarios for each participant.

Participants were also given demographic questions (age, sex, race, ethnicity, education) as well as questions relevant to political affiliation, voting behavior, and religion. Political affiliation questions included a question asking for the extent to which they identify with being a Republican or Democrat (1 – Strong Republican to 4 – Independent to 7 – Strong Democrat) ($M = 4.29$, $SD = 1.86$), one’s political party, how conservative/liberal (rated 1 – Very Conservative to 7 – Very Liberal) participants were on economic issues ($M = 4.21$, $SD = 1.88$) and economic issues ($M = 4.62$, $SD = 1.92$), and who the participant voted for (if anyone) in the 2016 Presidential election. Religious questions asked how religious the participant was (1

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– Not at All Religious to 9 – Extremely Religious) and also how spiritual the participant was (also 1 to 9) (religiosity items were meant for exploratory analyses and are not discussed further in this paper.) Finally, participants were asked if at any point during the experiment, they “stopped trying and started mindlessly picking answers”. For this final “attention” question, they were told that they would be paid regardless of their answer.

Procedure

The experiment was designed and implemented using Qualtrics software (Qualtrics, Provo, UT). After consenting to the study, participants were asked to

“... imagine scenarios involving current or potential social problems and decide between two plans developed by politicians in Congress meant to address them. Some plans will have been proposed along party lines with Democrats favoring one and Republicans favoring another (I will tell you which party has proposed which plan.) Other plans may be bipartisan - with no particular party preferring one over the other (in this case I will refer to each plan as "Plan A" and "Plan B".)”

Participants then made decisions (and confidence ratings) on each of the twelve risky-choice framing scenarios. Presentation order of the scenarios was randomized for each participant. After completing the decision task, participants answered demographic questions.

Results

Pre-registered Analysis

All analyses were conducted using the R software package (R Core Team, 2017) and RStudio (RStudio Team, 2016). A total of 18 participants admitted to not paying attention and thus their data were not analyzed (leaving the final N at 182).

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In order to test for effects of Frame (Gain, Loss), Party Support (Bipartisan, Republican Sure Option, Democrat Sure Option), and Party Identification (Strong Republican to Independent to Strong Democrat) on risky-choice, I conducted a Bayesian mixed-effects logistic regression with these factors (and all interactions) predicting participants' binary decisions (0 = Sure, 1 = Risky). Individual random (i.e., group-level) effects were included for participant and framing scenario. The analysis was conducted using the *brms* R package (Bürkner, 2017a) and data was processed using the *tidybayes* R package (Kay, 2018). I relied on default priors for all model parameters (improper flat priors for fixed (population) effects, half *student's-t* priors with 3 *df* and a scale parameter of 10 for random (group) effects and the intercept; Bürkner, 2017b). The model was fit using four chains of 1,000 iterations, with a burn-in of 1,000 iterations, leaving a total of 4,000 posterior samples.

As shown in Table 1, participants were more likely to choose the risky option in the loss frame ($M_{Gain} = 0.29, SE = 0.04, 95\% HDI [0.22, 0.38]$; $M_{Loss} = 0.61, SE = 0.46, 95\% HDI [0.52, 0.70]$).¹ The only other parameter estimates that did not include zero in the 95% *HDI* were the interactions between Party Support and Party ID. In the Republican Sure condition, probability of choosing the risky option

¹ For those who prefer the frequentist approach, a frequentist mixed-effects logistic regression is available in Table S1 in the Supplemental Materials. The preregistered analysis was originally for a frequentist approach, but the author decided to report a Bayesian analysis after the fact (both approaches yield very similar parameter estimates.)

increased with identification with the Democratic Party and in the Democrat Sure condition the reverse was true (see *Figure 1*.)²

Table 1. Bayesian Logistic Mixed Effects Model Predicting Decision

<i>Predictors</i>	<i>Log Odds</i>	<i>SE</i>	<i>95% HDI</i>	<i>Odds Ratio</i>
Intercept	-0.88	0.20	-1.25 – -0.46	0.41
Loss Frame	1.34	0.19	0.96 – 1.71	3.82
Republican Sure Option	0.11	0.18	-0.25 – 0.49	1.12
Democrat Sure Option	-0.12	0.19	-0.50 – 0.26	0.89
Party Identification	-0.19	0.20	-0.56 – 0.19	0.82
Loss X Republican Sure	-0.09	0.27	-0.62 – 0.41	0.92
Loss X Democrat Sure	-0.28	0.27	-0.77 – 0.28	0.75
Loss X Party ID	0.11	0.19	-0.28 – 0.46	1.11
Republican Sure X Party ID	0.58	0.19	0.20 – 0.96	1.79
Democrat Sure X Party ID	-0.57	0.19	-0.95 – -0.20	0.57
Loss X Republican Sure X Party ID	-0.02	0.28	-0.54 – 0.50	0.98
Loss X Democrat Sure X Party ID	-0.05	0.26	-0.60 – 0.45	0.95
Random (Group) Effects				
<i>SD</i> _{ResponseId}	1.86			
<i>SD</i> _{scenarioDec}	0.13			
Observations	2184			
Bayes R ²	0.372			

Note: Parameter Estimates with 95% HDIs that do not cross zero are bolded. For this analysis, *SE* is defined as the standard deviation of the posterior distribution.

² For the preregistered analysis I focused on party ID. However, the pattern of results remained consistent whether the Party ID variable was switched out for the variable measuring how conservative one is on economic issues or social issues (see Figure S1 in Supplemental Materials.)

Figure 1. Estimated probabilities (and 95% HDIs) of choosing risky option for each level of partisan identification (z-transformed) and for each manipulation of party support (Bipartisan plans, Republicans supports sure option, Democrats support sure option). All plots made with ggplot2 (Wickham, 2009).

A model comparison between the fully crossed model and a simplified model excluding the interaction terms involving frame was conducted using leave-one-out information criterion (looic; see Vehtari, Gelman, & Gabry, 2017a; 2017b; Yao, Vehtari, Simpson, & Gelman, 2018). The comparison yielded a better fit for the simplified model ($looic = 2,240.23$, $SE = 45.87$) than the fully crossed model ($looic = 2,246.97$, $SE = 46.24$; $Diff = 6.75$, $SE_{Diff} = 2.83$). Overall, the results of the model comparison (as well as an examination of the parameter estimates from the full model in Table 1) support the hypothesis that the effect of frame and the interactive effect of Party ID and Party Support are best captured by an additive model (see Figure 2).

Figure 2. Estimated probability of choosing the risky option (and 95% HDIs) broken down by all three factors (Frame X Party Support X Party ID (z-transformed)). Whereas the slope of the lines differ between Party Support conditions, note that the framing effect remains consistent, thus supporting an additive, rather than an interactive, model.

Comparing Clinton and Trump Voters (Not Preregistered)

I repeated the previous analysis, replacing the Party ID variable with whether the participant chose Hillary Clinton or Donald Trump in the 2016 Presidential election. For this analysis I limited participants to those who voted and those who chose either Clinton or Trump, reducing the sample to 120. Results mirrored those of the previous analysis, with Trump voters favoring Republican policy proposals and Clinton voters favoring Democratic proposals while also demonstrating a standard framing effect across all conditions (see Figure 3).

Figure 3. Estimated probability of choosing the risky option (and 95% HDIs). As in Figure 2, the framing effect persists as overall risk preference shifts based on which candidate they voted for and which party preferred the sure versus risky option (see Table A1 for full regression table).

Discussion

In this experiment, I examined how two different sources of bias – partisan identity and gain-loss frame – influenced risky-choice. Whereas risky-choice framing scenarios are generally non-specific regarding the source of each proposed option, in real-world situations it is common for proposals to come from multiple sources. In the case of public policy in the United States, it is extremely common for those sources to be differentiated based on the two major political parties. Results showed that risk preferences shifted in line with partisan loyalty. When a decision-maker’s preferred party supported a riskless proposal, they in turn became more risk-averse and when it supported the risky proposal, they became more risk seeking. Despite the clear effect of partisan bias, the standard framing effect (more risk-seeking in the loss frame compared to the gain frame) remained intact.

Implications for Dual-process Theories

Standard dual-process theories predict that activation of System 2 processing should yield a reduction in framing (De Martino, Kumaran, Seymour, & Dolan, 2006; Kahneman & Frederick, 2007). This could either result from conflicting intuitions (e.g., attraction to the more emotionally appealing frame versus the automatic attraction to one's political in-group), or from motivated cognition (e.g., a biased reasoning process that encourages partisan loyalty). In contrast to this prediction (regardless of the proposed mechanism for System 2 activation), this experiment found that the effect of partisan loyalty operated independently of frame.

Whereas this result is not easily accounted for by standard dual-process explanations for framing, it may not be so detrimental for an alternative dual-process theory – fuzzy-trace theory (FTT; Reyna, 2012). FTT suggests that framing results from a reliance on mental representations of each frame that do not reflect the precise verbatim information in each problem, but rather a useful representation that captures the overall gist of the options. In the case of risky-choice framing, the gist of the problem usually boils down to categorical distinctions between saving some/saving none for gains and losing some/losing none for losses (Chick, Reyna, & Corbin, 2016; Kühberger & Tanner, 2010; Reyna & Brainerd, 1995). Unlike the verbatim representation of the problem, in which saving 200 is mathematically equivalent to losing 400 (given an endowment of 600), the gist representation of the gain and loss frames are meaningfully distinct, and therefore there is no perceived logical violation in responding differently to each frame.

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FTT does not make clear predictions regarding the effect of motivational forces (in this case, partisanship) on representational complexity. For example, if one is motivated to choose the risky option in the gain frame, one could represent the problem ordinally, as “Some saved versus more saved”, which favors the risky option in the gain frame and the sure option in the loss frame (“Some lost versus more lost”). FTT predicts that adolescents, who tend to be more reward sensitive, are more likely to rely on this representation and therefore demonstrate a reversal of the standard framing effect (Reyna, Chick, Corbin, & Hsia, 2014; Reyna et al., 2011). Therefore, FTT could possibly account for either pattern of results in this experiment, suggesting the need for further work on the extent to which motivational forces (beyond reward sensitivity) can influence mental representation in FTT’s account of risky-choice framing.

Bias and Risk-Preferences Show No Asymmetry

Consistent with the results of Ditto et al. (2018), which showed symmetry in partisan bias across a range of tasks, results from this experiment suggested that bias in favor of one’s own party is also symmetrical with respect to risky-choice. Moreover, susceptibility to framing also appeared to be symmetrical across party. Whereas some research demonstrates that liberals and conservatives differ with respect to their sensitivity to threat and loss (see Jost, Glaser, Kruglanski, & Sulloway, 2003) the results from this experiment serves as an example of a number of domains (e.g., partisan bias, framing, and overall risk preference) in which party affiliation is not predictive.

Limitations

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It is worth noting that although I manipulated frame and which political party generated which option (sure versus risky), this experiment also relied on self-reported political party ID. Although party preference is a common (and necessary) variable in studies that examine partisan bias, it is still worth noting that this variable suffers from endogeneity, and therefore, causal conclusions should come with a grain of salt. Also, to achieve relative balance across party ID, I oversampled at both ends of the political spectrum. Therefore, if one wishes to generalize these results to the population level, it is crucial to take into account that these data are likely not a highly accurate representation in terms of party affiliation.

Given constraints on financial resources, I limited the manipulations of party support (for sure or risky option) to the three situations that allowed me to compare conflicts between partisan bias and framing (e.g., Republicans endorse sure/Democrats endorse risky; Democrats endorse sure/Republicans endorse risky; Bipartisan). However, this is not a fully factorial design. I could have included 6 more conditions combining Bipartisan options with Democrat and Republican options as well as including scenarios in which both options are proposed by a single party.

Finally, it is worth keeping in mind that the probabilities and outcomes used in this experiment were very limited in range. All risky options were carved into thirds (e.g., a 1/3 chance saving \$x and a 2/3 chance saving/losing \$x) and the endowments ranged from 180 lives at risk to 3,000 lives at risk for the lives problems and from \$12 million to \$600 million for the money problems. Prior work

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has shown that both probabilities and outcomes can influence risk preferences (though framing effects tend to be robust for reasonably large values; Kühberger, Schulte-Mecklenbeck, & Perner, 1999; Reyna et al., 2011), so future work concerned with partisanship and risk-preference should incorporate a wider set of probability/outcome pairs.

Conclusion

Real world policy proposals in government generally come from a source which can be labeled somewhere on the liberal-conservative political spectrum. Typical risky-choice framing studies use fairly generic scenarios in order to avoid any outside sources of bias. I was interested in how a political context might influence framing. Whereas standard dual-process theories would predict that partisan bias should overwhelm the effect of frame (by activating System 2 processing), results showed that both forms of bias operated independently. Beyond theoretical conclusions, this result shows that risk preferences for policy proposals that deal with large numbers of lives or large amounts of money at risk can be influenced both in response to the frame in which the policy proposal is couched and based on the political origins of the proposal.

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Supplemental Materials*Table S1. Frequentist Logistic Mixed Effects Model Predicting Decision with Party ID*

<i>Predictors</i>	<i>Log Odds</i>	<i>SE</i>	<i>95% CI</i>	<i>Odds Ratio</i>
Intercept	-0.81	0.17	-1.15 – -0.47	0.45
Loss Frame	1.20***	0.11	0.98 – 1.42	3.32
Republican Sure Option	0.07	0.13	-0.19 – 0.32	1.07
Democrat Sure Option	-0.25	0.13	-0.51 – 0.00	0.78
Party Identification	-0.14	0.16	-0.46 – 0.18	0.87
Republican Sure X Party ID	0.56***	0.13	0.30 – 0.82	1.75
Democrat Sure X Party ID	-0.59***	0.13	-0.85 – -0.33	0.56
Random (Group) Effects				
<i>SD</i> _{ResponseId}	1.76			
<i>SD</i> _{scenarioDec}	0.09			
Observations	2184			
Marginal R ² / Conditional R ²	0.089 / 0.53			

*Note: Full model failed to converge, thus I ran the model only including Party Support X Party ID interaction. Comparing full model (run despite convergence failure) to partial model demonstrated that the full model failed to fit the data better than the partial model $\chi^2(5) = 1.70, p = 0.889$. * $p < .05$, ** $p < .01$, *** $p < .001$*

Table S2. Bayesian Logistic Mixed Effects Model Predicting Decision with Presidential Vote in the 2016 Election

<i>Predictors</i>	<i>Log Odds</i>	<i>SE</i>	<i>95% HDI</i>	<i>Odds Ratio</i>
Intercept	-0.67	0.36	-1.40 – 0.06	0.51
Loss Frame	1.47	0.36	0.75 – 2.16	4.33
Republican Sure Option	-0.14	0.36	-0.85 – 0.55	0.54
Democrat Sure Option	0.76	0.35	0.08 – 1.44	0.50
Vote Clinton	-0.06	0.48	-1.00 – 0.91	0.95
Loss X Republican Sure	-0.61	0.49	-1.58 – 0.38	0.54
Loss X Democrat Sure	-0.69	0.50	-1.68 – 0.27	0.50
Loss X Vote Clinton	-0.32	0.46	-1.23 – 0.58	0.73
Republican Sure X Vote Clinton	0.58	0.47	-0.32 – 1.51	1.77
Democrat Sure X Vote Clinton	-1.62	0.47	-2.55 – -0.69	0.20
Loss X Republican Sure X Party ID	0.74	0.65	-0.56 – 1.98	2.10
Loss X Democrat Sure X Party ID	0.80	0.65	-0.46 – 2.07	2.21
Random (Group) Effects				
$SD_{ResponseID}$	1.81			
$SD_{scenarioDec}$	0.11			
Observations	1,440			
Bayes R ²	0.359			

Note: Parameter Estimates that have 95% HDIs that do not cross zero are bolded. For this analysis, SE is defined as the standard deviation of the posterior distribution.

FRAME, PARTISAN BIAS, AND RISKY-CHOICE

Table S3. Frequentist Logistic Mixed Effects Model Predicting Decision with Presidential Vote in 2016 Election

<i>Predictors</i>	<i>Log Odds</i>	<i>SE</i>	<i>95% CI</i>	<i>Odds Ratio</i>
Intercept	-0.50	0.30	-1.09 – 0.09	0.61
Loss Frame	1.12***	0.13	0.85 – 1.38	3.05
Republican Sure Option	-0.45	0.24	-0.92 – 0.03	0.64
Democrat Sure Option	0.42	0.24	-0.06 – 0.89	1.52
Clinton Voter	0.21	0.39	-0.96 – 0.55	0.81
Republican Sure X Clinton Voter	0.94***	0.32	0.31 – 1.56	2.55
Democrat Sure X Clinton Voter	-1.19***	0.32	-1.83 – -0.57	0.30
Random (Group) Effects				
<i>SD</i> Responseld	1.69			
<i>SD</i> scenarioDec	0.0003			
Observations	1,440			
Marginal R ² / Conditional R ²	0.081 / 0.507			

*Note: Full model failed to converge, thus I ran the model only including Party Support X Party ID interaction. Comparing full model (run despite convergence failure) to partial model demonstrated that the full model failed to fit the data better than the partial model $\chi^2(5) = 3.06, p = 0.691$. * $p < .05$, ** $p < .01$, *** $p < .001$*

FRAME, PARTISAN BIAS, AND RISKY-CHOICE

Figure S1. Estimated probabilities (and 95% HDIs) of choosing risk option from full factorial Bayesian Logistic Mixed Effects Models predicting choice with A: Economic Ideology and B: Social Ideology (both predictors were z-transformed).