Supplementary Information

1 Survey Design

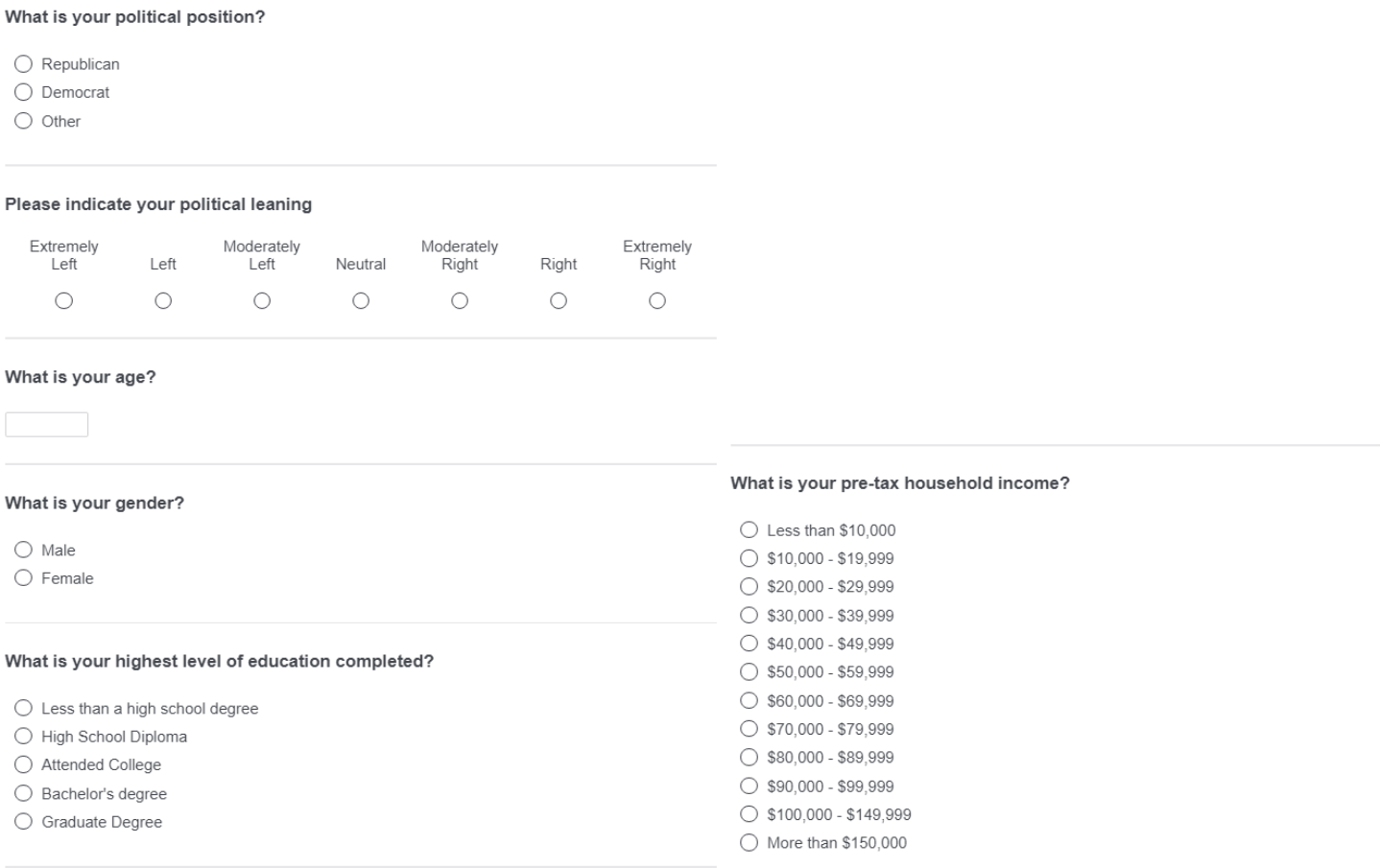

Figure 1.1: Demographics Questions. Only left-leaning Democrats and right-leaning Republicans are allowed to complete the survey.

Bonus

We have independently researched whether the news stories shown to you is true. **The truth may be any rating between 1 and 7.** In addition, you will also be provided with the answer from another participant. Both your initial answer and your updated answer matter to your bonus!

Note: The bonus value of a question will be specified at each question (e.g. "This question is worth **X**"). **If you are exactly correct, you receive $X. The closer your answer, the higher your bonus!**

After completing the survey, we promise to calculate and distribute your bonus within one week!

I have reviewed information above.

◯ Yes

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The following is the mathematical rule to calculate bonus: **In short, the more accurate your answer, the higher the bonus! Since a small improvement in accuracy will yield higher bonus, it's also worth leveraging other people's answer to improve your judgment if you believe other's answers are good.**

The following mathematical rule also prevents hedging answers. You just need to know that you should give your best possible answer for each question to get optimal bonus..

news accuracy bonus1 = X - 2*|initial rating - correct answer|^2
news accuracy bonus2 = X - 2*|updated rating - correct answer|^2
news bonus = a uniformly random draw of news accuracy bonus1 and news accuracy bonus2
probability bonus1 = X - 10*|initial probability - correct probability|^2
probability bonus2 = X - 10*|updated probability - correct probability|^2
probability bonus = a uniformly random draw of probability bonus1 and probability bonus2

Total bonus = news bonus + probability bonus

Figure 1.2: Bonus Instructions

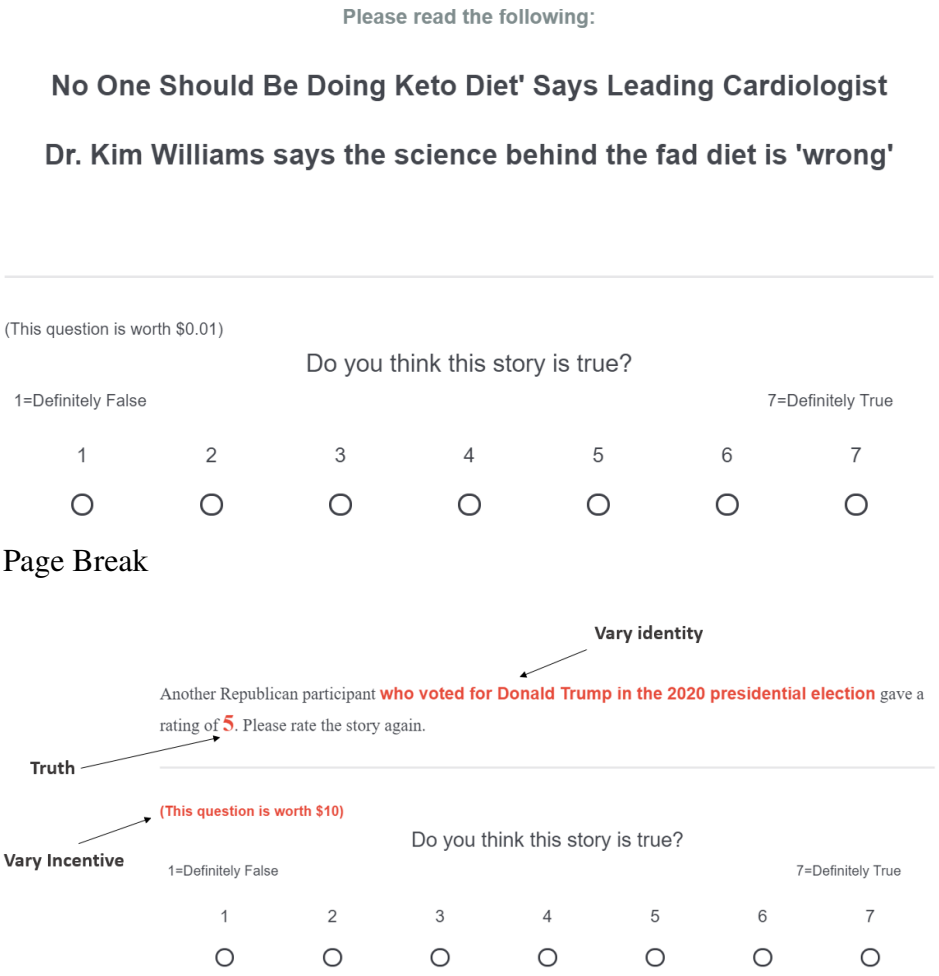

Figure 1.3: News Rating Task Example (Initial Answer + Updated Answer)

In the previous study, **100 Republican voters** and **100 Democratic voters** completed a similar news veracity rating task (they each rated three news). We first calculate the average accuracy of their news ratings. Then randomly match the Republicans with Democrats to form **100 pairs** and compare the two performances within each pair. We want to know whether you think Republicans or Democrats performed better overall.

One party performed better if it had more accurate members out of the 100 paired comparisons. For example, one party performed better if its members were more accurate in 51 out of 100 pairs of comparisons.

◯ I have carefully reviewed information above.

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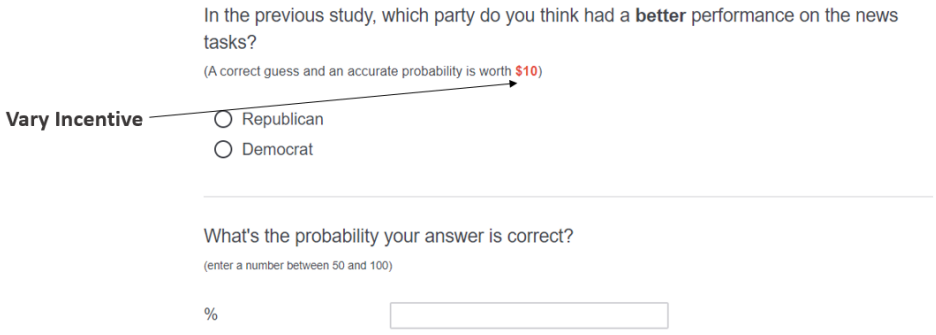
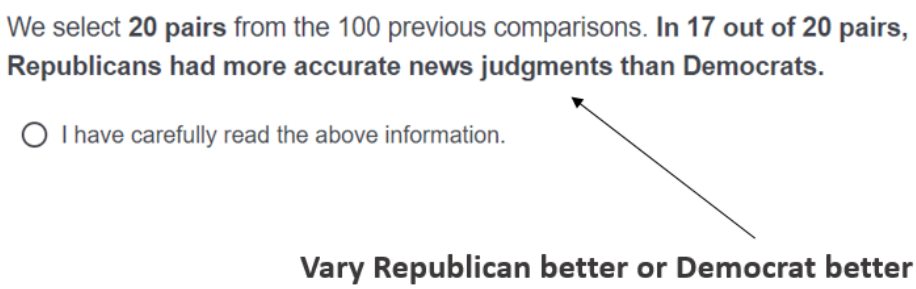


Figure 1.4: Partisan Competence Prior Belief Elicitation



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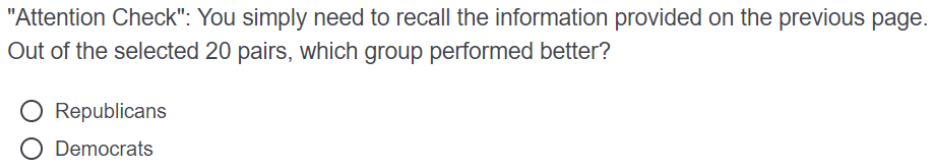

Page Break. Subjects were screened out if they answered the attention check incorrectly.

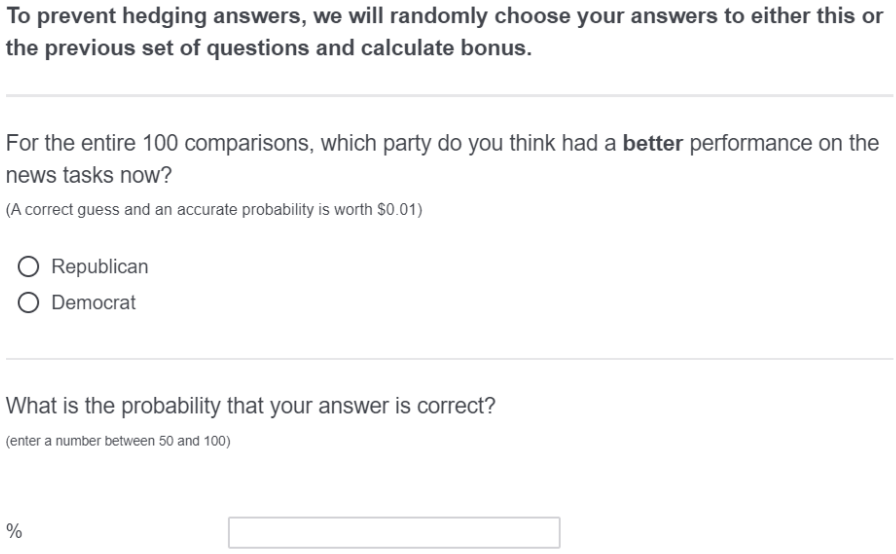

Figure 1.5: Partisan Competence Posterior Belief Elicitation

2 News Headlines in the Main Task

News Headline	Fact Checker Rating
Michael Bublé says he is quitting music following his son's cancer battle: 'I don't have the stomach for it anymore' In an interview with the Daily Mail's Weekend Magazine published on Saturday, Michael Bublé talked retirement and said he "doesn't have the stomach" for the celebrity lifestyle anymore.	4
Sick Kids Hospital Toronto will euthanize children with or without parental consent. A recent report from the Hospital for Sick Children in Toronto states that they are not only ready to do euthanasia on children but their policy states that a child should be able to die by euthanasia without the consent or knowledge of the parents.	4.33
Report: Kim Kardashian Is Allegedly Planning to Divorce Kanye A shocking new report from Us Weekly seems to confirm the bad news, claiming Kim has been "feeling trapped" in her marriage for some time and is plotting her exit. According to sources, Kim is playing the "supportive wife" during Kanye's recovery, but is low key laying the groundwork to file for a divorce and keep full custody of her kids in the meantime.	3
Meghan Markle and Kate Middleton: Pregnant? Due on the Same Day?! We recently discussed the report that Meghan Markle is expecting a boy and a girl – fraternal twins – with Prince Harry.	3.33
No One Should Be Doing Keto Diet' Says Leading Cardiologist Dr. Kim Williams says the science behind the fad diet is 'wrong'	5

Queen invites Meghan Markle's mum Doria to spend Christmas with royal family in offer never extended to Kate's relatives The Queen is said to have asked Doria to join the Royal Family for Christmas as a 'mark of her respect' for the duchess.	5
All Of The Harry Potter Films Are Officially Coming To Netflix Messenger Netflix has announced that all eight of the Harry Potter films will be available to stream	5.33
A Giant 500ft Asteroid Is 'Heading For Earth At 20,000mph' What sounds more pleasant than a huge space rock flying towards us at 20,000mph? We'll tell you exactly what - the fact that it's expected to 'skim past' Earth. *Wipes brow*	5.33
No evidence' having high levels of bad cholesterol causes heart disease, claim 17 physicians as they call on doctors to 'abandon' statins No evidence exists to prove that having high levels of bad cholesterol causes heart disease, leading physicians have claimed.	4.67
How Sunscreen Could Be Causing Skin Cancer, Not The Sun Summer may be a long way off, but it's never too early to start thinking about protecting your skin. For most people, this means covering themselves in sunscreen, which corporate marketing campaigns encourage at every turn. Yet, while we do indeed need protection to prevent sunburns, blocking out the sun entirely is not ideal. Rich in vitamin D, it offers a number of other health benefits, including, oddly enough, cancer prevention. We've been made to fear the sun, and, as a result, adults and children are choosing to drench themselves in a bath of toxic, hormone-disrupting chemicals.	4.67

Table 1: The ten news headlines used in the main News Rating Task. The $< /p >$ and $< br >$ were used for formatting in the Qualtrics survey.

Headline	Dem Rating	Rep Rating	Cohen's d	Two sample t-test p-value.
1	4.17	3.73	0.22	0.04
2	1.32	1.85	0.36	0.001
3	5.37	5.1	0.15	0.17
4	2.41	2.46	0.03	0.79
5	4.65	4.5	0.09	0.42
6	3.42	3.69	0.14	0.22
7	3.97	4.28	0.15	0.19
8	4.26	4.05	0.1	0.37
9	2.55	2.9	0.18	0.11
10	2.96	4.31	0.71	0.001

Table 2: "Dem Rating" and "Rep Rating" are Democrats' and Republicans' average initial news veracity ratings. "Cohen's d" measures the size of difference between Democrats' and Republicans' initial news ratings. Cohen's d between 0.2 and 0.5 (small effect), between 0.5 and 0.8 (medium effect), greater than 0.8 (large effect). The last column lists the p-value of a two-sample t-test of Democrats' and Republicans' initial news ratings.

3 Main Results and Alternative Variable Specification

All predictors are centered and all binary variables are coded as 1 and -1.

3.1 Main Regression Results and Main Regression with Alternative DV

Scaled amount of update is the DV used for the main analysis used in the main text. WOA is the weight on advice. Amount of update is the absolute amount of updating in the direction of the advice.

Table 3: Main Results with Alternative DVs

	Dependent variable:		
	Scaled Amount of Update	WOA	Amount of Update
	(1)	(2)	(3)
Counter-partisan Advisor (1 = Yes)	-0.017^{**}	-0.017^{*}	-0.043^{+}
	(0.005)	(0.007)	(0.024)
High Incentive (1 = Yes)	0.008	0.020^{**}	0.045^{+}
	(0.005)	(0.007)	(0.024)
Right	0.001	0.007^{***}	0.025^{***}
	(0.002)	(0.002)	(0.007)
Counter * High Incentive	-0.003	-0.007	-0.021
	(0.005)	(0.007)	(0.024)
Counter * Right	0.006^{***}	0.007^{***}	0.020^{**}
	(0.002)	(0.002)	(0.007)
High Incentive * Right	0.0001	0.001	-0.005
	(0.002)	(0.002)	(0.007)
Counter * High Incentive * Right	-0.003^{+}	-0.005^{*}	-0.016^{*}
	(0.002)	(0.002)	(0.007)
Constant	0.091^{***}	0.206^{***}	0.486^{***}
	(0.005)	(0.007)	(0.024)
Observations	2,763	2,763	2,763
R^2	0.017	0.018	0.016
Adjusted R^2	0.014	0.016	0.013
Residual Std. Error (df = 2755)	0.248	0.343	1.087

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

3.2 Main Regression Results Including Subjects whose Initial Distance is 0

In the previous regression, we remove subjects whose initial distance is 0 (i.e., initial answer = influence). This is a robustness check including these subjects.

Table 4: Main Results: Including Subjects whose Initial Distance is 0

	Dependent variable:		
	Scaled Amount of Update	WOA	Amount of Update
	(1)	(2)	(3)
Counter-partisan Advisor (1 = Yes)	-0.030^{***}	-0.016^{*}	-0.056^{*}
	(0.007)	(0.006)	(0.022)
High Incentive (1 = Yes)	0.002	0.018^{**}	0.036^{+}
	(0.007)	(0.006)	(0.022)
Right	-0.0001	0.006^{**}	0.019^{**}
	(0.002)	(0.002)	(0.007)
Counter * High Incentive	-0.002	-0.005	-0.016
	(0.007)	(0.006)	(0.022)
Counter * Right	0.007^{**}	0.006^{**}	0.018^{**}
	(0.002)	(0.002)	(0.007)
High Incentive * Right	-0.001	0.0001	-0.006
	(0.002)	(0.002)	(0.007)
Counter * High Incentive * Right	-0.001	-0.003^{+}	-0.011^{+}
	(0.002)	(0.002)	(0.007)
Constant	0.032^{***}	0.176^{***}	0.370^{***}
	(0.007)	(0.006)	(0.022)
Observations	3,206	3,206	3,206
R^2	0.014	0.014	0.013
Adjusted R^2	0.011	0.012	0.011
Residual Std. Error (df = 3198)	0.369	0.326	1.075

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

3.3 Main Regression with Subjects' Partisanship (Binary)

Instead of using subjects' right-wing extremity, we use subjects' partisanship, which is a binary classification.

Table 5: Main Results: Binary Classification of Subjects' Partisanship

	Dependent variable:		
	Scaled Amount of Update	WOA	Amount of Update
	(1)	(2)	(3)
Counter-partisan Advisor (1 = Yes)	-0.024^{***}	-0.025^{***}	-0.066^{**}
	(0.005)	(0.007)	(0.021)
High Incentive (1 = Yes)	0.008	0.019^{**}	0.051^{*}
	(0.005)	(0.007)	(0.021)
Republican (1 = Yes)	0.005	0.021^{**}	0.069^{***}
	(0.005)	(0.007)	(0.021)
Counter * High Incentive	-0.0003	-0.002	-0.003
	(0.005)	(0.007)	(0.021)
Counter * Right	0.019^{***}	0.024^{***}	0.063^{**}
	(0.005)	(0.007)	(0.021)
High Incentive * Right	0.003	0.003	-0.013
	(0.005)	(0.007)	(0.021)
Counter * High Incentive * Right	-0.008^{+}	-0.013^{*}	-0.044^{*}
	(0.005)	(0.007)	(0.021)
Constant	0.089^{***}	0.198^{***}	0.457^{***}
	(0.005)	(0.007)	(0.021)
Observations	2,763	2,763	2,763
R^2	0.017	0.018	0.015
Adjusted R^2	0.015	0.016	0.013
Residual Std. Error (df = 2755)	0.248	0.343	1.087

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

3.4 Prior Belief of Partisan Competence

Table 6: Task 2 Results: Prior Belief Elicitation Task

	Dependent variable:
	Probability of Co-partisans Being Better
High Prior Incentive (1 = Yes)	−0.034
	(0.370)
Right	−1.889***
	(0.109)
High Prior Incentive * Right	−0.018
	(0.109)
Constant	58.350***
	(0.370)
Observations	3,206
R^2	0.089
Adjusted R^2	0.088
Residual Std. Error	18.075 (df = 3202)

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

Table 7: Task 2 Results: Binary Subjects' Partisanship Instead of Right-wing extremity

	Dependent variable:
	Probability of Co-partisans Being Better
High Prior Incentive (1 = Yes)	−0.006
	(0.317)
Republican	−6.019***
	(0.317)
High Prior Incentive * Republican	−0.104
	(0.317)
Constant	60.462***
	(0.317)
Observations	3,206
R^2	0.101
Adjusted R^2	0.100
Residual Std. Error	17.955 (df = 3202)

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

3.5 Change in Belief of Partisan Competence

Table 8: Task 3 Results

	Dependent variable:
	Change in Probability of Co-partisans Being Better
Feedback (1 = Counter-Partisan-Better)	-16.295^{***}
	(0.425)
High Prior Incentive (1 = Yes)	0.273
	(0.425)
Right	0.445^{***}
	(0.128)
Feedback * High Prior Incentive	-0.228
	(0.425)
Feedback * Right	-0.231^{+}
	(0.128)
High Prior Incentive * Right	-0.058
	(0.128)
Feedback * High Prior Incentive * Right	-0.067
	(0.128)
Constant	-2.589^{***}
	(0.425)
Observations	3,206
R^2	0.362
Adjusted R^2	0.361
Residual Std. Error	21.405 (df = 3198)

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

Table 9: Task 3 Results: Binary Subjects' Partisanship Instead of Right-wing extremity

	Dependent variable:
	Change in Probability of Co-partisans Being Better
Feedback (1 = Counter-Partisan-Better)	-16.032^{***}
	(0.379)
High Prior Incentive (1 = Yes)	0.333
	(0.379)
Republican	1.519^{***}
	(0.379)
Feedback * High Prior Incentive	-0.155
	(0.379)
Feedback * Republican	-0.667^{+}
	(0.379)
High Prior Incentive * Republican	-0.109
	(0.379)
Feedback * High Prior Incentive * Republican	-0.258
	(0.379)
Constant	-3.087^{***}
	(0.379)
Observations	3,206
R^2	0.363
Adjusted R^2	0.361
Residual Std. Error	21.393 (df = 3198)

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

4 Prior Probability of Co-Partisan Performed Better

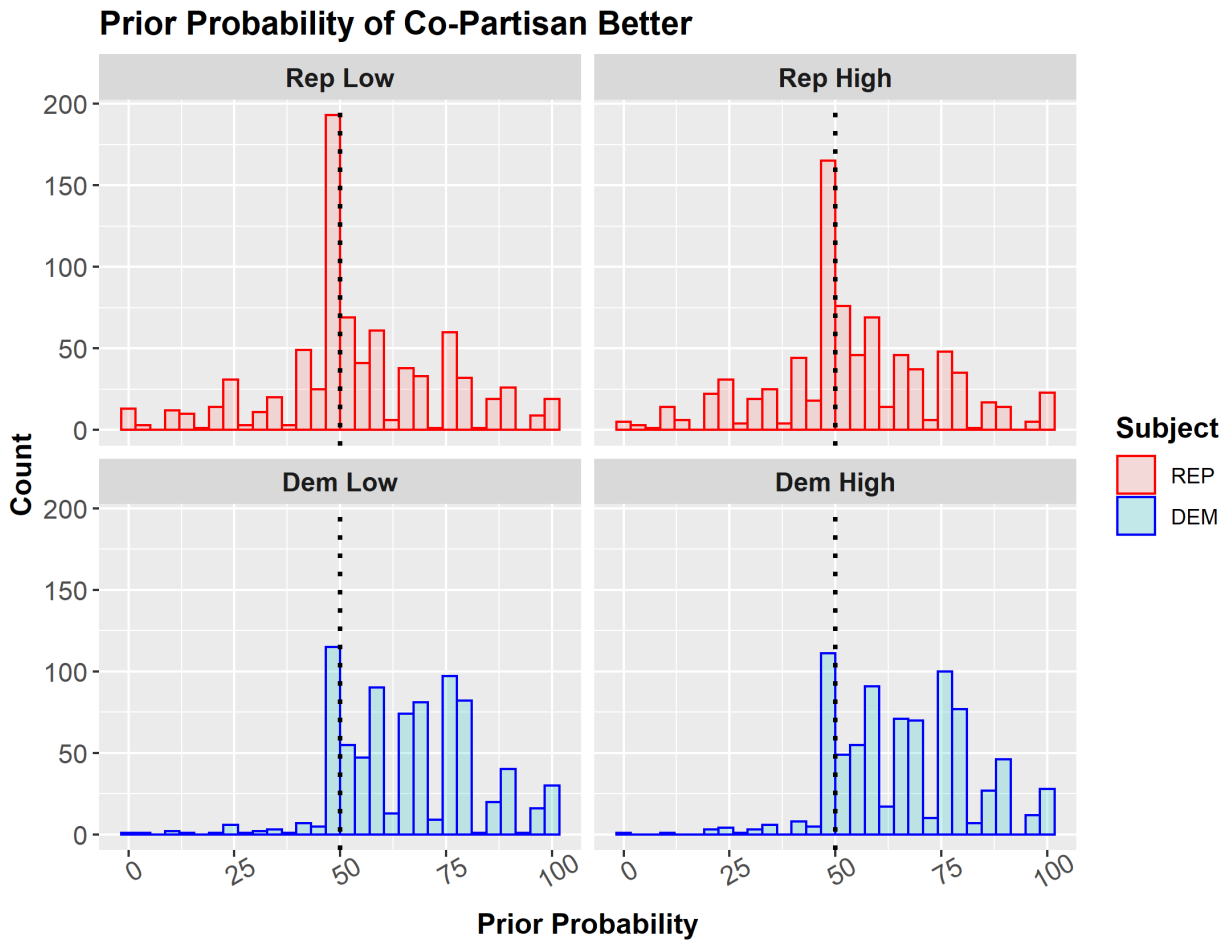

Figure 4.1: The upper and lower panel plot the histograms Republican and Democratic subjects' prior probability of their own party performing better in the news rating task given high vs low stake during prior elicitation. There is a peak at 50% which suggests that our binary choice scheme does not prevent subjects from stating their indifferent opinion if they believe Republicans and Democrats are equally competent.

5 Posterior Belief Given Feedback vs Bayesian Benchmark

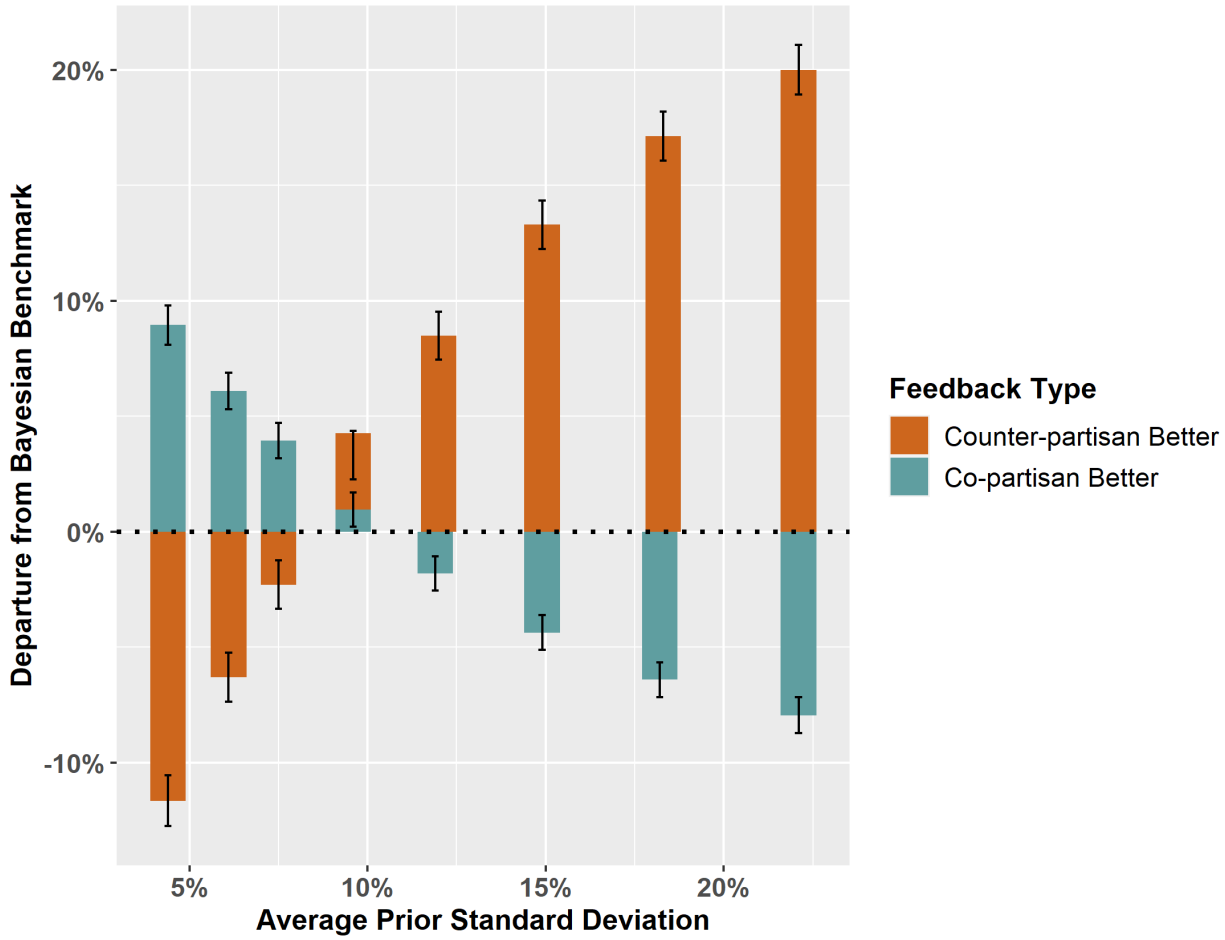

Figure 5.1: Whether a subject exhibits under- or over-updating relative to a Bayesian benchmark given certain types of feedback depends on the standard deviation of their prior (Beta) distribution. Shown is subjects' departure from a Bayesian benchmark under different levels of standard deviation associated with their Beta Distribution. Error bars indicate 95% confidence intervals.

We examine whether Republican and Democratic subjects exhibit asymmetric updating after receiving performance feedback. To construct the Bayesian benchmark, we assume that subjects' prior probability of their own party being more accurate than their counter-party follows a Beta distribution $\sim$ Beta (a, b). The posterior has a closed form solution captured by the beta-binomial conjugacy. If the feedback is 17 co-partisans being more accurate out of the 20 selected subjects, the Bayesian posterior should be Beta (a+17, b+3). If the feedback is 17 counter-partisans being more accurate out of the 20 selected subjects, the Bayesian posterior should be Beta (a+3,

b+17). We assume subjects report the expected value of the Beta Distribution as a point estimate of the probability that their co-partisans were more accurate. We calculate our variable of interest - departure from Bayesian benchmark - using actual posterior probability minus Bayesian posterior. Therefore, a positive (negative) departure from Bayesian benchmark given co-partisan-better feedback means the subjects over-update (under-update), which is in favor of their own party (counter-party). A positive (negative) departure from Bayesian benchmark given counter-partisan-better feedback means the subjects under-update (over-update), which is in favor of their own party (counter-party).

To construct a Bayesian benchmark, we need to pin down the hyperparameters of subjects' prior distribution. Although we have the expected value of each subject's prior distribution (i.e., their reported probability), we are not informed about the variance of their prior distribution. For example, a subject has a prior belief that there is a 70% probability her own party performed better in the news rating task. Then her prior could follow Beta (7, 3) or Beta (70, 30), both of which have the same expected value of 70% but different variances as well as different corresponding Bayesian benchmarks. Therefore, in the following figure, we examine subjects' departure from their Bayesian benchmark under different variance of Beta Distribution, holding the expected value of the distribution to be their reported probability. More specifically, we set a = 100 * reported probability / k and b = (100 - 100 * reported probability) / k, with k = 1, 2, 3, 5, 8, 13, 21, 34. A larger k corresponds to a larger prior variance, meaning subjects having larger uncertainty of their initial reported probability. The results suggest that if we assume subjects are certain about their reported probability (small k), they exhibit over-updating given a feedback (e.g., they are too optimistic about their co-partisan's performance given a co-partisan better feedback and too pessimistic about their co-partisan's performance given a counter-partisan better feedback). As we assume a larger uncertainty of subjects' reported probability (large k), the patterns reverse such that they exhibit under-updating given a feedback (e.g., they are too pessimistic about their co-partisan's performance given a co-partisan better feedback and too optimistic about their co-partisan's performance given a counter-partisan better feedback. Therefore, unless we have exact information

about subjects' prior distribution, we can not make definitive conclusions about whether subjects are selectively processing the feedback in a motivated fashion.

6 Separate Analysis of Republicans and Democrats in News Rating Task

Table 10: Main Results

	Dependent variable:
	Scaled Amount of Update
Counter-partisan Advisor (1 = Yes)	−0.005
	(0.007)
High Incentive (1 = Yes)	0.010
	(0.007)
Counter * High Incentive	−0.008
	(0.007)
Constant	0.095***
	(0.007)
Observations	1,365
R^2	0.003
Adjusted R^2	0.001
Residual Std. Error	0.259 (df = 1361)

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

Table 11: Main Results

	Dependent variable:
	Scaled Amount of Update
Counter-partisan Advisor (1 = Yes)	-0.042^{***}
	(0.006)
High Incentive (1 = Yes)	0.005
	(0.006)
Counter * High Incentive	0.008
	(0.006)
Constant	0.084^{***}
	(0.006)
Observations	1,398
R^2	0.033
Adjusted R^2	0.031
Residual Std. Error	0.235 (df = 1394)

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

7 Other Robustness Checks

All main results are robust under the robustness checks in this section.

Table 12: Main Results: News Rating Task (Removing News 2 and News 10)

	Dependent variable:		
	Scaled Amount of Update	WOA	Amount of Update
	(1)	(2)	(3)
Counter-partisan Advisor (1 = Yes)	-0.024^{***}	-0.026^{**}	-0.073^{**}
	(0.006)	(0.008)	(0.027)
High Incentive (1 = Yes)	0.006	0.019^{*}	0.049^{+}
	(0.006)	(0.008)	(0.027)
Right	0.001	0.006^{*}	0.023^{**}
	(0.002)	(0.003)	(0.008)
Counter * High Incentive	0.0002	-0.004	-0.018
	(0.006)	(0.008)	(0.027)
Counter * Right	0.005^{**}	0.006^{*}	0.015^{+}
	(0.002)	(0.003)	(0.008)
High Incentive * Right	0.0003	0.001	-0.002
	(0.002)	(0.003)	(0.008)
Counter * High Incentive * Right	-0.003	-0.004^{+}	-0.016^{*}
	(0.002)	(0.003)	(0.008)
Constant	0.096^{***}	0.219^{***}	0.508^{***}
	(0.006)	(0.008)	(0.027)
Observations	2,186	2,186	2,186
R^2	0.019	0.019	0.016
Adjusted R^2	0.015	0.015	0.013
Residual Std. Error (df = 2178)	0.256	0.352	1.105

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

Table 13: Main Results: News Rating Task (only MTurk subjects)

	Dependent variable:		
	Scaled Amount of Update	WOA	Amount of Update
	(1)	(2)	(3)
Counter-partisan Advisor (1 = Yes)	-0.017^{**}	-0.022^{*}	-0.072^{**}
	(0.006)	(0.009)	(0.027)
High Incentive (1 = Yes)	0.015^{*}	0.021^{*}	0.043
	(0.006)	(0.009)	(0.027)
Right	0.001	0.007^{**}	0.022^{**}
	(0.002)	(0.003)	(0.008)
Counter * High Incentive	0.004	-0.002	0.002
	(0.006)	(0.009)	(0.027)
Counter * Right	0.004^{*}	0.004	0.007
	(0.002)	(0.003)	(0.008)
High Incentive * Right	0.0005	-0.001	-0.011
	(0.002)	(0.003)	(0.008)
Counter * High Incentive * Right	-0.002	-0.003	-0.013
	(0.002)	(0.003)	(0.008)
Constant	0.093^{***}	0.202^{***}	0.468^{***}
	(0.006)	(0.009)	(0.027)
Observations	2,020	2,020	2,020
R^2	0.015	0.017	0.016
Adjusted R^2	0.011	0.014	0.013
Residual Std. Error (df = 2012)	0.241	0.339	1.037

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

Table 14: Task 2 Results: Prior Elicitation (Only MTurk Subjects)

	Dependent variable:
	Probability of Co-partisans Being Better
High Prior Incentive (1 = Yes)	0.054
	(0.449)
Right	-1.852^{***}
	(0.130)
High Prior Incentive * Right	0.032
	(0.130)
Constant	58.668^{***}
	(0.449)
Observations	2,342
R^2	0.085
Adjusted R^2	0.084
Residual Std. Error	18.161 (df = 2338)

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

Table 15: Task 3 Results: Change in Belief (Only MTurk Subjects)

	Dependent variable:
	Change in Probability of Co-partisans Being Better
Feedback (1 = Counter-Partisan-Better)	-16.609^{***}
	(0.510)
High Prior Incentive (1 = Yes)	-0.050
	(0.510)
Right	0.470^{**}
	(0.149)
Feedback * High Prior Incentive	-0.732
	(0.510)
Feedback * Right	-0.253^{+}
	(0.149)
High Prior Incentive * Right	-0.210
	(0.149)
Feedback * High Prior Incentive * Right	-0.062
	(0.149)
Constant	-3.033^{***}
	(0.510)
Observations	2,342
R^2	0.373
Adjusted R^2	0.371
Residual Std. Error	21.315 (df = 2334)

Notes: $^{+}$p<0.1, *p<0.05; **p<0.01; ***p<0.001.
Robust standard errors in parentheses.

8 A High-level Illustration of the Identification Strategy

First, we assume that the preference-based account in advice-taking exists only when incentive is low (e.g., the final rating worths \$0.01)[1]; and we assume a final rating worths \$10 is enough to reduce (or crowd-out) the preference-based motivations and induce the subjects to focus on the accuracy motives in advice-taking. Second, let's define some notations.

$Dev_{i,c,id}$: a subject i's amount of advice-taking after seeing the rating by an advisor with a particular id under an incentive level m for the final rating. In addition, a subscript $id = co$ means the subject receives an influence from a co-partisan; a subscript $id = counter$ means the subject receives an influence from a counter-partisan; a subscript $m = low$ means a subject is assigned to the low incentive condition; a subscript $m = high$ means a subject is assigned to the high incentive condition.

$\gamma_{i,m}$: the factors which vary across individual and monetary incentive level, e.g. subjects may exert more effort in advice-taking when the stake is high, which may lead them to take more or less advice;

$\alpha_{i,id}$: the factors vary across individual and advisor identity, e.g. subjects have different priors regarding the advisor identity – the accuracy motive which depends on subjects' prior of the advisor's competence is captured by $\alpha_{i,id}$.

ε_i: the factors which vary across individuals, e.g. subjects have different competence in the task.

$Pref.Mot_{i,m,id}$: the effect of preference-based motivations.

[1] we do not have to worry about preference-based account is eliminated by \$0.01 because if that is the case, preference-based motivations would not be a concerning problem

The advice-taking can be captured by:

$$Dev_{i,m,id} = Pref.Mot_{i,m,id} + \alpha_{i,id} + \gamma_{i,m} + \varepsilon_i \tag{8.1}$$

We need to use a "difference-in-difference" or the interaction term in the regression to identify preference-based motivations. The first-difference is taken within the assigned advisor identity (co- vs. counter-partisan), which removes the effect advisor identity and the effect of individual noise on advice-taking.

$$\begin{aligned}
&Dev_{i,m=low,id=counter} - Dev_{i,m=high,id=counter} \\
&= Pref.Mot_{i,m=low,id=counter} + \delta_{i,id=counter} + \gamma_{i,m=low} + \varepsilon_i - (\delta_{i,id=counter} + \gamma_{i,m=high} + \varepsilon_i) \\
&= Pref.Mot_{i,m=low,id=counter} + \gamma_{i,low} - \gamma_{i,high}
\end{aligned}$$

Similarly,

$$\begin{aligned}
&Dev_{i,m=low,id=co} - Dev_{i,m=high,id=co} \\
&= Pref.Mot_{i,m=low,id=co} + \delta_{i,id=co} + \gamma_{i,m=high} + \varepsilon_i - (\delta_{i,id=s} + \gamma_{i,m=high} + \varepsilon_i) \\
&= Pref.Mot_{i,m=low,id=co} + \gamma_{i,low} - \gamma_{i,high}
\end{aligned}$$

Then we take the difference of the first difference and yield

$$\begin{aligned}
&\left(Dev_{i,m=low,id=counter} - Dev_{i,m=high,id=counter}\right) - \left(Dev_{i,m=low,id=co} - Dev_{i,m=high,id=co}\right) \\
&= Pref.Mot_{i,m=low,id=counter} - Pref.Mot_{i,m=low,id=co} + \gamma_{i,low} - \gamma_{i,high} - (\gamma_{i,low} - \gamma_{i,high}) \\
&= Pref.Mot_{i,m=low,id=counter}
\end{aligned}$$

The resulting $Pref.Mot_{i,m=low,id=counter}$ is the effect of preference-based motivation when subjects are taking advice from a counter-partisan in the low incentive condition, which is what we are trying to identify. The intuition of the identification strategy - given the preference-based account exists - is that subjects are more swayed by counter-partisan advice when the monetary incentive is large, but their advice-taking from a co-partisan is relatively less affected by the level of incentive, which we argue is due to larger stakes offsetting subjects' preference-based motivations against counter-partisan advice. In addition, any confound factors introduced by the varying incentive which also affects advice-taking (e.g., higher stakes cause people to be more serious about the task and take more advice, which is not preference-based motivation) is canceled out by the interaction of advisor identity and incentive level (difference-in-difference): if people are taking more advice from a counter-partisan purely because they are more serious about the task due to the higher incentive, they should do so to the same extent given a co-partisan advice (because they are more serious about the task). Hence, confounding factors like this are addressed by our identification strategy.