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# Essays on Information and Beliefs

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by

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The Dissertation of ChienHsun Lin is approved.

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Essays on Information and Beliefs

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**Abstract**

Essays on Information and Beliefs

by

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This dissertation examines how people update their beliefs with different information structures under various environments. The first chapter studies how the self-selection of COVID-19 vaccine information affects people's belief updates on vaccine effectiveness and their preferences for vaccines. Rational information acquisition theory predicts people select the more informative information; thus people's beliefs will be more persuaded by the information they select. We test the prediction in a critical real-world context—information about COVID-19 vaccines. We conduct an online experiment in Taiwan where the subjects select information about COVID-19 vaccines, and then the subjects update their beliefs about the vaccine effectiveness and references of vaccines. As our design distinguishes different stages of the rational acquisition framework, it allows us to diagnose the underlying mechanism of the theory. Our empirical findings demonstrate evidence that people's information acquisition generally coheres with the rational theory framework predictions; that is, people choose information when the information is more likely to alter their decisions. We show that our subjects' beliefs change more when they see the information they select. We also find evidence of change in vaccine preferences and choices after they receive the information they select, which further suggests that the subjects follow the rational information acquisition framework. Chapter 2 studies whether the first vote changes how people's voting decisions after seeing information. The first vote can be a crucial political assertion that causes people to stick to their beliefs even after reading the information. In this study, we examine the interaction of voting experience and the persuasiveness of information. To control the potential endogeneity arising from the self-selection to vote, we use eligibility as the random cutoff, as the ineligible voters can never select to vote. We utilized the 2021 Taiwanese Referendum to see whether new information heterogeneously impacts people's voting choices between eligible and ineligible voters. We find that the eligible subjects become less supportive when they see negative information about nuclear power plants and more supportive when they see positive information about algal reefs. The treatments make the eligible *nay* voters in nuclear power plants and *yea* voters in algal reefs stick on their votes more, suggesting the confirming effect of the action of voting. The heterogeneity between eligible and ineligible subjects is more profound among the subjects who care about environmental issues the most, which indicates that the first vote can be an active assertion to environmental voters. In the third chapter, we explore how individuals use and value different statistical features in a balls-in-boxes experiment. In contrast to the literature, people in the real world are usually exposed to summarized information (e.g., proportion) instead of the raw data they can access in the laboratory. In our belief updating experiment, we experimentally investigate how individuals use and value different statistical characteristics of realized signals, referred to as sample features. We find that people align the closest to the Bayesian updating when they see Proportion. We also see people prefer Proportion same as Count or Sequence, even though Proportion is less informative than the other two features. Furthermore, we find that the belief updates are closer to the Bayesian benchmark when the subjects use their preferred sample feature, implying that people are sophisticated about the subjective value of information.

Keywords: belief update, information, vaccine, referendum

JEL codes: D83, C91, D90

# Permissions and Attributions

1. The content of chapter 1 and appendices A, B, and C is the result of a collaboration with Hans Tung.
2. The content of chapter 2 and appendices D and E is the result of a collaboration with Ming-Jen Lin.
3. The content of chapter 3 and appendices F and G is the result of a collaboration with Menglong Guan, Jing Zhou, and Ravi Vora.

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# Chapter 1

# Self-selection of Vaccine Information and Belief Update

*with Hans Tung*

## 1.1 Introduction

Information shapes our beliefs and guides our decisions. Previously, studies have examined information's influence on beliefs in diverse fields such as education, politics, and real estate pricing (Wiswall and Zafar (2015); Chopra et al. (2022); Fuster et al. (2022)), belief's influence on decisions in social distancing during COVID-19 (Allcott et al. (2020)), and information's influence on decisions in vaccine taking (Alsan and Eichmeyer (2021)). While sometimes information is exposed to people passively, people also actively acquire information by themselves. One of the leading theory frameworks explaining the acquisition for information is the instrumental value of information (Bohnenblust et al. (1949), Blackwell (1953)). In this standard theory setting, the information with higher instrumental value yields posterior beliefs that induces higher expected utility under optimal decisions. If the instrumental value of the information exceeds the cost of gathering information, the decision makers will acquire the information. In other words, people gather information if the information can persuade them to take different actions to improve their welfare. Hence, the theory predicts that the *acquired* or *selected* information is more informative, so people should update their beliefs more when they see the information they select.

However, the connection between information selection and belief change remains unclear in empirical settings. To better illustrate this issue, we provide an example. Consider Amelia, who is deciding whether to receive a vaccine. Before making the decision, Amelia can seek a noisy and costly signal of the vaccine from some information source (*e.g.*, spending an hour on reading reports on scientific journals). If Amelia believes the vaccine is ineffective and does not want to take it, then she has to see a strong signal supporting this vaccine to convince her that taking this vaccine is better than not taking any vaccine. Hence, she may not acquire the information about the vaccine from this source if the cost of the information is too high. Therefore, under the rational information acquisition framework, the self-selected information must persuade Amelia's belief about the vaccine effectiveness more. Nonetheless, we cannot observe how Amelia would update with the information *not selected*. If Amelia underestimates the effectiveness of the vaccine or is overconfident about her belief, she will never update her beliefs about the vaccine through this information source. To a policy maker who wants to avoid the potential inefficiency from not receiving the optimal vaccine or to mitigate the radicalization from the agent's misbelief, it is important to identify the update in beliefs from the (un)selected information.

In this chapter, we examine how the self-selection of information affect people's belief update and decision making with a controlled experiment of COVID-19 vaccine information acquisition, which is a high-impact real-world context. Specifically, we conduct an online survey experiment in Taiwan utilizing the context of the vaccines, where we elicited their consumption of information, and we surveyed the subjects of their beliefs of vaccine effectiveness and vaccine preference. The three elements enclosed in the experiment construct the complete flow in the information acquisition framework: information selection, belief update, and decisions based on beliefs. The context of COVID-19 vaccines helps us evaluate the outstretch of the classical information acquisition framework, especially in a field context with natural language. Furthermore, our controlled environment allows us to exclude other factors that could come in and affect the belief updates from the information (*e.g.*, the complexity or accessibility of information). With the treatment design, we can also solve the endogeneity from the selection and evaluate the unobserved counter-factorial in the field data. The most importantly, by dissecting the rational information acquisition framework into steps, we can tackle down and analyze the mechanism behind the scene, which enables us to diagnose the applicability the framework.

The experiment has four main phases. In Phase 1, the subjects state their pre-treatment beliefs about the vaccine effectiveness and their preferences for the vaccines. In Phase 2, the subjects rank the information about the effectiveness of among five different brands of COVID-19 vaccines according to their willingness to read, and then they select the information about the (up to three) vaccines they want to read. In Phase 3, we present the effectiveness information of different vaccines to the subjects, where the assignment of vaccine information is independent of their information selections. Lastly, in Phase 4, we ask about the post-treatment belief about the vaccine effectiveness and the post-treatment preferences.

We document the main empirical findings from three aspects. *(i) information selection*: we find that the subjects are more willing to read and select the vaccine information if they believe the vaccine is more effective. *(ii) belief update*: the subjects' beliefs are changed more by the information if they receive the information they select, controlling the disagreement between the information and their prior beliefs. *(iii) updated decision*: when the subjects receive the selected vaccine information, their preference of that vaccine increases, and more people will consider that vaccine, which suggests that the information may contribute in terms of exclusive margin. The three main findings cohere with the rational information acquisition framework. Combing other behavioral patterns we find in our data, we claim that rational information acquisition framework explains people's behavior in our vaccine information selection scenario.

While we find most of the results align with the theory prediction, we identify that some subjects may perform sub-optimally in the information selection stage. The theory framework predicts that the subjects should select the information about the vaccines that they have less precise beliefs about (so that the information can help reduce more uncertainty); however, we find that the subjects tend to choose the information about the vaccines that they are more familiar about. This phenomenon cannot be explained by the choice set (people only paying attention to available vaccines in Taiwan) or the choice confirming (people choose the information about vaccines that they have received). This finding resonates with the past studies that people usually mis-infer the information value in terms of how much uncertainty can the information resolve (Ambuehl and Li, 2018b).

As our environment allows the information selection and belief update of multiple vaccines, we also introduce a model that incorporate correlated beliefs. This captures subjects' beliefs that some vaccines may be correlated (for example, there can be some similarity between Pfizer and Moderna as they are both MRNA vaccines), and people can have indirect belief update from other information sources. We document from our data that people do update from other information they see when the information of the very vaccine is not available, and the degree of updates depreciates, which aligns with the prediction.

We contribute to the literature in three ways. First, we extend the scope of rational information acquisition theory to the setting of COVID-19 vaccines, which regards crucial public health consequences. We show that the framework is generally applicable even in a complicated environment with multiple vaccines and various attributes, where we not only care about the accuracy of beliefs, but also about the decisions induced by the beliefs and information.

Second, our design dissect the theory framework into steps, which allows us to carefully diagnose each step in information acquisition problem. In the context of this chapter, we document that the subject can correctly evaluate the information from the aspect of vaccine effectiveness (which relates to the welfare from the decisions), while they may be less sensitive to the information's instrumental value of reducing uncertainty. However, different behavior biases may present in other contexts. With our design, we can examine the mechanism of the phenomenons from the observational data. This is especially important for the policy evaluation; the policy makers can apply this methodology to solve the issues identified in the specific steps diagnosed.

Lastly, we develop an incentive-compatible approach to elicit the relative preference for different pieces of information. When the subjects truthfully reveal their preference of reading information about vaccines, they are also more likely to receive the information that they are interested in, without introducing monetary incentives. In addition, since the subjects can still be randomly assigned the information, we can investigate the treatment effect exogenously. The methodology is especially suitable for contexts where monetary incentives are not applicable, *e.g.* studies under political contexts. Furthermore, removing additional incentives may simplify the experiment and hence reduce the uncertainty of the measurements.

### 1.1.1 Literature

Besides the laboratory setting, there is growing literature investigating people's demand for information in real-world scenarios. Hoffman (2016) recruits businesspeople experts and lets them evaluate the value of the information about the price of websites. Chopra et al. (2022) examine whether fact-checking affects people's demand for news, and they find heterogeneity of fact-checking on demand by ideology.

One natural question that emerges from the literature is whether there is any connection between information demand and belief updating. Fuster et al. (2022) find that there is heterogeneity in information demand, and the subjects' posteriors do change based on the information consumed. They also find that lowering the cost decreases the dispersion in posterior beliefs. However, as they provide only the most preferred information, it is still unclear how the preference for information influences the belief updates, especially for the *undemanded* information.

Our study also provides another piece of investigation on how people update beliefs and decisions under real-world contexts (*e.g.*, Wiswall and Zafar (2015) on college major choices; Hoffman (2016) on website evaluation; Haaland and Roth (2021) on racial discrimination). Furthermore, we contribute to the strand of literature discussing how information affects people's behavior during the COVID-19 pandemic (*e.g.*, Van Bavel et al. (2022) on the endorsement and public health behavior; Sadish et al. (2021) on different delivery of the pandemic-related information; Banerjee et al. (2020) on the endorsement from experts).

The chapter proceeds as follows. In the next section, we describe the experimental design. In section 1.3, we provide a theoretical model of information consumption and the belief update, and we will provide predictions that we may observe in the experiment. Section 1.4 summarizes the data set and the main variables, and section 1.5 presents the main analysis. Then we conclude in section 1.6.

## 1.2 Background and Experimental Design

Under the real-world context, people's information consumption can be determined by how much they are interested in the information. Hence, the real-world information consumption data can suffer from the selection issue. For instance, when people only acquire the interested information, we cannot observe the information not acquired; however, the interests about information can be an unobserved variable that affects their belief updates. To separate the effects of information consumption from preferences, we need to create an environment that can elicit people's information preferences while making people receive the information regardless of their preferences of information.

In this experiment, we let the subjects state their preferences for vaccine information. Then the subjects are assigned into treatment arms—in some of the treatment groups, the subjects were assigned the vaccine information that they demanded, while in other treatment groups, the subjects are randomly assigned to some vaccine information. With this design, the subjects are (non-monetarily) incentivized to state their true preferences, and they are still possible to be exposed to the not preferred information. In the rest of the section, we will discuss the background of the experiment, and then we describe the design and the detail of the experiment.

### 1.2.1 Background

**COVID-19 Vaccines**

Approximately six months after the sequence of the COVID-19 virus as identified, the first COVID-19 vaccine, *CanSino*, was approved by the Chinese government for emergency use on June 24th, 2020. Since then, more and more vaccines have been developed to help mitigate the outbreak of the COVID-19 pandemic. As the full authorization of vaccines usually takes years of phases of trials, most of the governments granted *Emergency Use Authorization* (EUA) to the vaccines that passed certain criteria, including Phase III trials proving the safety and effectiveness of vaccines.[1]

By November 2021, there were five vaccines initiated in Phase IV trials. Sinovac (CoronaVac, *Sinovac* henceforth) was one of the earliest authorized vaccines, which utilized the inactive virus. Oxford-AstraZeneca (Vaxzevria, *AstraZeneca* henceforth) and Janssen (Jcovden, *J&J* henceforth) utilize viral vector to deliver the genetic information for producing antibodies, which is also a technical platform widely used in other vaccines. Pfizer-BioNTech (Comirnaty, *Pfizer* henceforth) and Moderna (Spikevax, *Moderna* henceforth) are mRNA vaccines. Pfizer and Moderna were the first vaccines that applied mRNA which were widely used among large populations. Since mRNA vaccines were relatively novel, the efficacy and side effects were uncertain to the public. There were also Taiwanese-developed vaccines; the MVC COVID-19 vaccine (*Medigen* henceforth) was the most received domestic vaccine in Taiwan.

**<u>The Pandemic and Vaccines in Taiwan</u>**

The first COVID-19 case in Taiwan was reported on January 21st, 2020. However, due to the strict border control and quarantine policy, the cases in Taiwan remained low ($<$ 1000 cases) until March 2021. Due to the spread of the Alpha variant of the COVID-19 virus, the total number of cases in Taiwan raised to 10,000 and killed more than 500 people by June 2021.

[1] In medical studies, the purpose of Phase III trials of clinical research is to examine efficacy and monitor the side effects, which typically requires 300-3,000 participants. Phase IV trials focus on safety and efficacy in a large population, which typically require several thousand participants. See https://www.fda.gov/patients/drug-development-process/step-3-clinical-research for details in the U.S.

The first COVID-19 vaccine authorized in Taiwan was AstraZeneca, which was authorized and provided in March 2021. The vaccines were prioritized to medical workers and elder people because of the limited supply. Although Taiwanese people were hesitant about taking vaccines because of the campaigns about the adverse events of vaccines, the surge in May 2021 in active cases and deaths pushed people to take the vaccines. By the end of June 2021, more than two million Taiwanese (approximately 10% of the population) received at least one dose of vaccine.

In November 2021 (the time when the experiment intervention was implemented), there were in total four vaccines in Taiwan available: AstraZeneca, Pfizer, Moderna, and Medigen. Taiwan's Center for Disease Control (CDC) authorized the mix-and-match reception between different vaccines in November 2021, partly to resolve the under-supply of the vaccines (especially for the non-domestic vaccines). This gave people incentive to seek different vaccine options. According to the CDC's record on November 22nd, there were 77.1% of the population have received at least one dose of vaccines and 48.9% of the population have received two doses. Although J&J and Sinovac were not granted EUA in Taiwan, some Taiwanese traveled overseas to receive vaccines. However, the record of non-authorized vaccines was not recognized by the CDC for control policies such as border control.

### 1.2.2 Details of the Experiment Design

**Vaccine Performance Information**

We provided the performance information about five COVID-19 vaccines. The five vaccines chosen are (in the order of the brand names): Johnson & Johnson, Moderna, Oxford-AstraZeneca, Pfizer, and Sinovac.[2] The reports are all published in scientific

[2] The five vaccines selected are the ones that satisfied the following two criteria in September 2021: (1) it has publicly revealed Phase 3 reports, and (2) it is currently under Phase 4. Please refer to Appendix

journals, which are publicly accessible on the WHO website.

For the information on efficacy and hospital prevention rates, we selected the latest statistics from the trials with the complete vaccine reception of recommended doses. For the information on the side effects, we selected the latest statistics from the reports that have both general side effects and severe (>Rank 3) side effects recorded.[3]

**Subject Recruitment**

We recruited the subjects with Facebook ads, which reached out to Facebook and Instagram Users in Taiwan whose ages are within the range of 17-64. When the subjects clicked the ad link, they were redirected to the survey page and then asked to finish the survey. After the subjects finished the survey, they would receive a flat payment of a gift card worth $5 USD ($150 Taiwanese Dollar).

We received a total of 1066 complete responses, excluding the subjects who reported age below 17 and above 64. The summary statistics of the subject pool are summarized in Appendix Section B1.[4] Table B1 summarizes the subject characteristics. Among the characteristics we listed, there is no single characteristic that meaningfully predicts the treatment assigned, which implies that the randomization is balanced.

**The Procedure of the Experiment**

The experiment was implemented with an online survey platform, Qualtrics. The estimated time duration of the survey is 20 minutes, and the median subject took around 15 minutes to finish the whole survey. Figure 1.1 depicts the flow of the experiment survey.

B. for detailed information.

[3]The information provided is summarized in Table B2.

[4]We address that our sample is younger than the user population in Taiwan. 43% of our sample are below 25, while 19% of the population are below 25; 87% of our sample are below 45, while 69% of the population are below 45. We also have more female respondents (63%) than the population, which is roughly (50%).

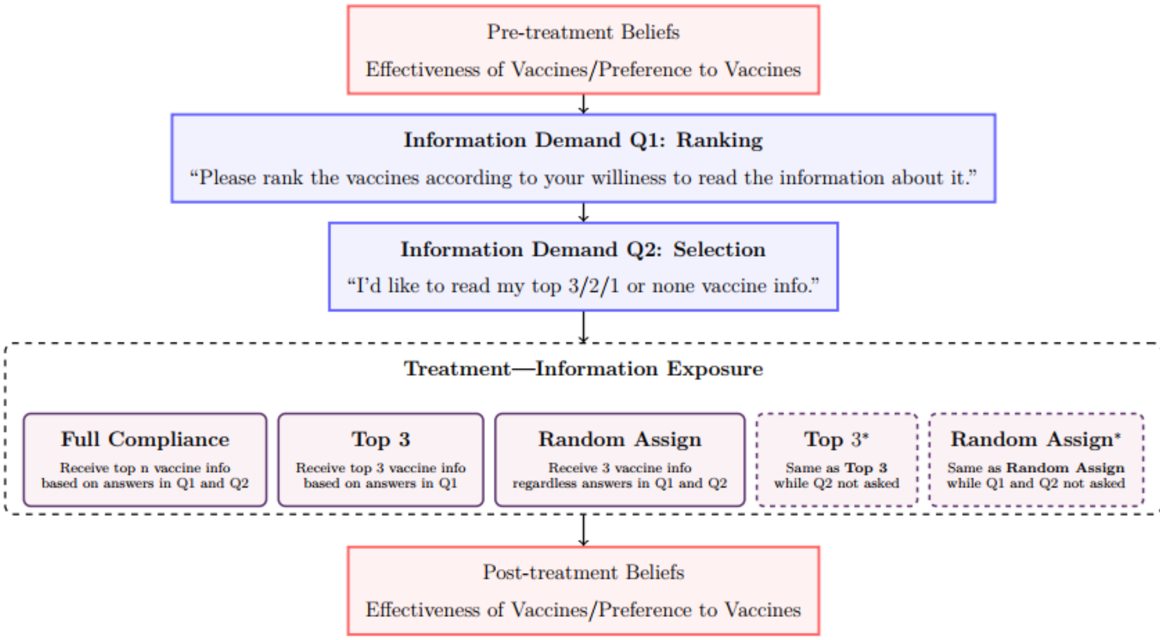



Figure 1.1: The Experiment Survey Flow

The experiment contains four main stages: (1) pre-treatment assessment, (2) information demand elicitation, (3) information treatment exposure, and (4) post-treatment assessment. In the pre-treatment assessment stage, the subjects stated their beliefs about the performance with respect to the characteristics of the vaccines–efficacy, hospitalization prevention rate, adverse event rate, and severe adverse event rate. Also, they were asked to state their preferences for the vaccines.

In the information demand elicitation stage, we told the subject that they would have a chance to read the vaccine information from the actual scientific reports. Figure 1.2 shows the screenshots of the sample interface subjects encountered. The subjects expressed their demand for vaccine information among five vaccines with the two (strategic method) questions:

(1) **[Ranking]** Please rank the listed five vaccines from the highest to the lowest based on how much you want to read the information about the vaccine.

(2) [**Selection**] You ranked X the 1st, Y the 2nd, and Z the 3rd. If you have the chance to select, would you like to read the information about your top 3, top 2, top 1, or 0 vaccines?

The subjects were told that these decisions would increase the probability of reading the information about the higher-ranked vaccines, so it's in their interests to state their true preferences.

In the information treatment exposure stage, the vaccine information was presented to the subjects. The subjects may receive information about different vaccines based on the treatment arms they were assigned, which will be explained in detail in the next paragraph. Figure 1.3 is an (English translated) sample of the information that subjects observed. Once the subjects access the information page, they can click the buttons to see the specific information. After they read the information, they were also asked how much they trusted the information, which parts of the information were unknown to them, and which parts were different from their original beliefs. Finally, in the post-treatment assessment stage, the subject answered the same set of questions in the pre-treatment assessments.

**Treatments**

In the information exposure stage, the subjects receive different sets of information according to the treatment arms they are assigned to. There are three main treatment arms and two supplementary treatment arms. The treatment arms determine whether a subject received the vaccine information based on their stated preferences in the treatment exposure stage. We list the three main treatment arms as follows:

- **Full Compliance (FC).** We provide the subjects with the vaccine information following subjects' both decisions in "Ranking" and "Selection" questions.

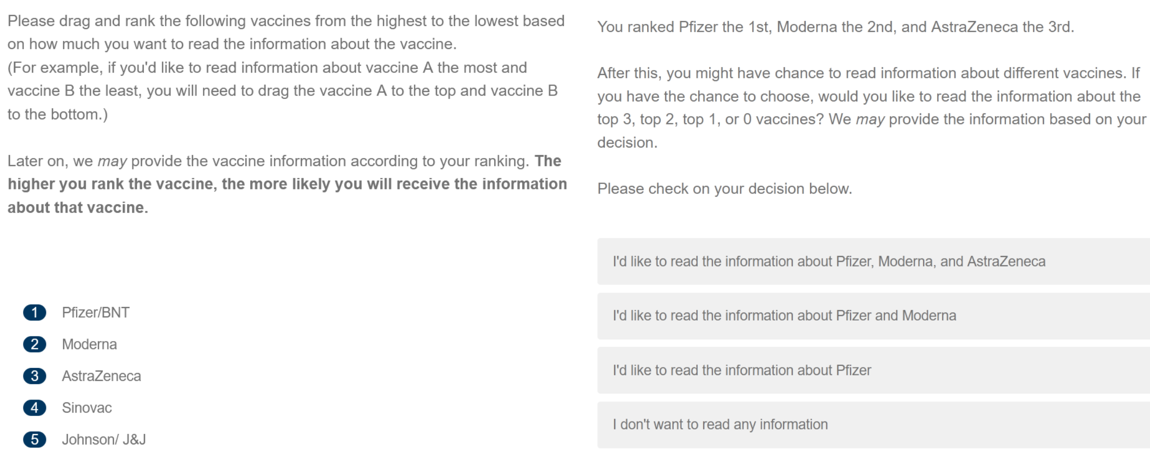



Figure 1.2: Vaccine Information Demand Elicitation


Figure 1.3: The Vaccine Information Page

- **Top 3 (T3).** We provide the subjects with all top-3-ranked vaccine information following only subjects' decisions in the "Ranking" question.

- **Random Assignment (RA).** We provide the subjects three random vaccine information independent to the information preference elicitation questions.

We provide an example here to illustrate the differences between treatments. Suppose a subject has the following ranking: (1) Pfizer (2) Moderna (3) AstraZeneca (4) J & J (5) Sinovac, and she *selects* only the top 2 vaccine information. If she is in the Full Compliance arm, she will receive only the information about Pfizer and Moderna, where both are *selected top 3 vaccines*;[5] if she is in the Top 3 arm, she will receive all three highest ranked vaccine information, *i.e.* Pfizer, Moderna, and AstraZeneca, where AstraZeneca is in top 3 but not acquired by the subject. If she is in the Random Assignment arm, she will receive information about three random vaccines.[6]

Note that if a subject ranks the vaccines and selects information following her true preference, it is more likely for her to receive the information which is ranked higher and is selected under this design. To see this, we can apply the previous example. Suppose the subjects has the same preference as stated. Since the subject ranks Pfizer at the top and selects it, she will definitely receive Pfizer information if she truthfully reports her preference information when she is in Full Compliance or Top 3 treatment arms. Contrarily, if she does not truthfully report the preference ranking and does not select it, she will not receive Pfizer information when she is in Full Compliance or Top 3 treatment arms. Furthermore, this demand elicitation and treatment assignment design allow us

[5]If a subject is assigned to the Full Compliance treatment chooses not to read any information sheet, she will skip the treatment exposure stage.

[6]In order to control the possible confusion from not receiving the information selected, we have two supplementary treatment arms, T3* and RA*. The subjects in the T3* treatment only saw the "Ranking" question (no "Selection"), and they only received the information about their top 3 vaccines (according to the "Ranking" question). The subjects in RA* Treatment did not see either of the "Ranking" and "Selection" questions, and they received the information about three random vaccines.

to independently assign information treatment regardless of the demands stated, as the subject can be assigned to the Random Assignment arm and receives information about three random vaccines, regardless of her preference.

We can categorize the vaccines into three groups, depending on the subjects' elicited information demands:

(1) *Selected Top 3*–the vaccine is on the subjects' top 3 and is selected

(2) *Non-selected Top 3*–the vaccine is on the subjects' top 3 but is not selected

(3) *Not Top 3*–the vaccine is not on the subjects' top 3

Within each of the three categories, whether the vaccine information is delivered to the subjects is randomly determined.[7] This helps us causally evaluate the treatment effect on belief updating from receiving the vaccine information among within each category. Then we can compare treatment effects among the three information demand categories.

## 1.3 Theoretic Framework

We apply the environment of COVID-19 vaccine information with the rational information acquisition framework, where our decision maker's (DM) vaccine information acquisition scenario into a three-stage decision.[8]

1. The DM decides whether to acquire costly information about the vaccine's effectiveness.

[7]We follow the same example. Suppose the subject puts Pfizer in the *Selected Top 3* category, the subject will not receive the vaccine information only if she is in RA treatment and the vaccine is not one of the three vaccines drawn. As whether the subject receives the information about the vaccine is fully determined by the randomness created by the experimenters, we can exclude the self-selection of the consumption within the *Selected Top 3* category. A similar argument applies to the other two categories.

[8]A similar setting can be found in Fuster et al. (2022), where they asked subjects to predict the housing price given information sources with different accuracy. They first let subjects choose the information source, then ask subjects to update their beliefs about the housing price, and finally pay the subjects based on how close their beliefs are to the true housing price.

2. The DM receives the information and updates the beliefs.

3. The DM decides whether to get vaccinated according to her beliefs.

In the rest of the section, we suppose the normally distributed beliefs of the vaccine effectiveness and assume the Bayesian updated belief after receiving the information.

### 1.3.1 The Case of Single Vaccine

#### Setting

For simplicity, we start with the case where there is only information for one vaccine available. The DM has a prior on the vaccine's overall effectiveness $\theta \sim N(\mu_\theta, \sigma_\theta^2)$, where $\mu_\theta$ and $\sigma_\theta^2$ are known.[9] Suppose $\overline{v}$ is the reservation value from the outside option.[10] When the DM does not acquire any information about the vaccine, she will refuse the vaccine if the reservation value is higher than the mean of her prior belief on vaccine effectiveness will take the vaccine otherwise. Thus the value that the DM receives without information, $v_0$, can be expressed as

$$v_0 = \max\{\overline{v}, \mu_\theta\}.$$

#### The Acquisition of the Information

The DM can also acquire a signal $s$ about the vaccine with a fixed cost $c$, where $s = \theta + \varepsilon$ and $\varepsilon \sim N(0, \sigma_s^2)$ with $\sigma_s^2$ is known to the DM. We further assume that $\theta \perp \varepsilon$. Hence $s|\theta \sim N(\theta, \sigma_s^2)$ and $s \sim N(\mu_\theta, \sigma_s^2 + \sigma_\theta^2)$.

[9] It can also be generalized to the case of $N$ vaccines following normal distribution where the variance-covariance matrices of the prior and the signals are diagonal; that is, there is no correlation between the priors and the signals among different vaccines.

[10] The reservation value can have multiple interpretations. Suppose an agent has decided to receive the vaccine which she believes is the most effective. Then the reservation value can be her prior of effectiveness of this vaccine. The other vaccine dominates the original one only if the posterior suggests that the new vaccine is (on average) better.

Given a realization of $s$, the Bayesian posterior belief becomes

$$\theta|s \sim N\left(\frac{\sigma_s^2\mu_\theta + \sigma_\theta^2 s}{\sigma_s^2 + \sigma_\theta^2}, \frac{\sigma_s^2\sigma_\theta^2}{\sigma_s^2 + \sigma_\theta^2}\right).$$

Lastly, the DM decides whether to receive the vaccine. The DM consumes the vaccine if $\mathbb{E}[\theta|s]$ exceeds the reservation value $\overline{v}$; in other words, she takes the vaccine if she believes taking the vaccine is better than not taking one after she reads the information. Therefore, after receiving the signal $s$, we define the value function as

$$v(s) = \begin{cases} \mathbb{E}[\theta|s] & \text{if } \mathbb{E}[\theta|s] \geq \overline{v} \\ \overline{v} & \text{if } \mathbb{E}[\theta|s] < \overline{v} \end{cases}. \tag{1.1}$$

Then we can find the expected value of acquiring the information. Note that

$$\mathbb{E}[\theta|s] \geq \overline{v} \;\Leftrightarrow\; s \geq \frac{(\sigma_\theta^2 + \sigma_s^2)\overline{v} - \sigma_s^2\mu_\theta}{\sigma_\theta^2} \equiv s^*,$$

where we define $s^*$ to be the critical value. When the signal ($s$) that the DM receives is higher than the critical value, she will take the vaccine since the signal implies a more optimistic posterior belief than the reservation value.

Figure 1.4 demonstrates a characterizing example of belief updating of vaccine effectiveness. The top panel plots the probability density of the random variable, $\theta$, which represents the vaccine effectiveness. The gray distribution represents the prior distribution, where $\mu_\theta$ is the mean of the prior distribution. $\overline{v}$ is the reservation value. In this example, since $\mu_\theta < \overline{v}$, the DM is not taking the vaccine when there is no information.

After receiving a signal of $s$, the belief is adjusted to the posterior distribution (the red curve). The mean of the posterior distribution is $\mathbb{E}[\theta|s]$. Since $\mathbb{E}[\theta|s]$ implied by the information ($s$) is higher than the reservation value, $\overline{v}$, the DM is persuaded to take

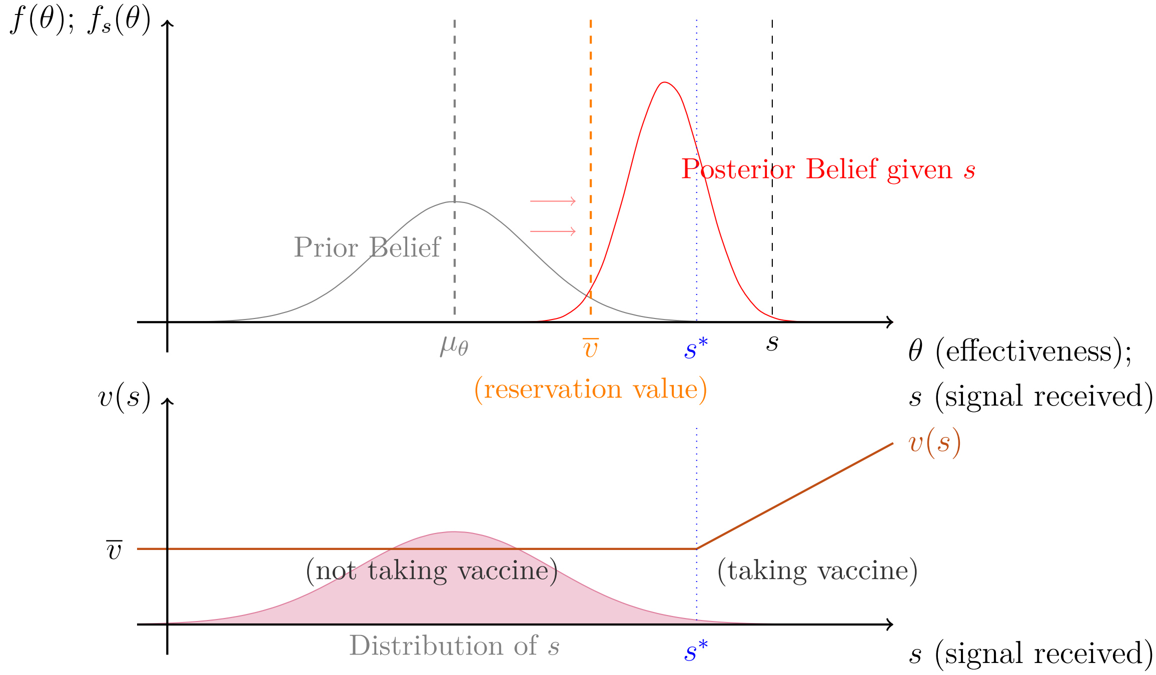



Figure 1.4: A Demonstration of the Belief Update in Vaccine Effectiveness

*Notes.* The top panel demonstrates the probability density of the vaccine effectiveness, $\theta$. The gray distribution represents the prior distribution, where $\mu_\theta$ is its mean. After receiving a signal of $s$, the belief is adjusted to the posterior distribution (the red curve). $\overline{v}$ is the reservation value; when the posterior mean exceeds $\overline{v}$, the DM will take the vaccine, and the expected value from taking it is $\mathbb{E}[\theta|s]$. $s^*$ is the critical signal that switches the DM's decision of taking the vaccine or not. The bottom figure demonstrates the value function after receiving the signal $s$. On the left of the critical signal $s^*$, the value is the reservation value $\overline{v}$, as the DM will not take the vaccine. On the right of $s^*$, the DM will take the vaccine, and the value becomes the expected efficacy, $\mathbb{E}[\theta|s]$.

the vaccine after receiving the information, and the expected value becomes $\mathbb{E}[\theta|s]$.[11] As elaborated above, the critical signal, $s^*$, is the threshold that determining whether the DM is persuaded to take the information. If $s \leq s^*$, then the DM is not persuaded to take the vaccine, and she gets the reservation value, $\overline{v}$. If $s > s^*$, then the DM is persuaded, and the value she gets becomes $\mathbb{E}[\theta|s]$. The bottom panel depicts the value with the information, $v(s)$.

As the distribution of $s$ is known to the DM, she can find the expected value of the value function, $\mathbb{E}_s[v(s)]$, prior to the decision of acquiring the information. Then the DM's decision of *whether to acquire the information* can be determined by the following criterion:

$$\begin{cases} \text{Acquire the information} & \text{if } \mathbb{E}_s[v(s)] - v_0 - c \geq 0 \\ \text{Refuse the information} & \text{otherwise} \end{cases}.$$

Therefore, we can study the behavior of *the value of the information* $(\mathbb{E}_s[v(s)] - v_0 - c)$ to determine the decision of the agent.

**Proposition.** Define the relative accuracy of the prior belief $\gamma \equiv \frac{\sigma_s^2}{\sigma_\theta^2}$. Let $V(\overline{v} - \mu_\theta, \gamma, c) \equiv \mathbb{E}_s[v(s)] - v_0 - c$ be the value of the information.

(a) $V(\cdot)$ decreases in $|\overline{v} - \mu_\theta|$.

(b) $V(\cdot)$ decreases in $\gamma$.

(c) $V(\cdot)$ decreases in $c$.

As $V(\cdot)$ increases, the agent will be more likely to acquire the information. Therefore, Proposition 1.3.1 implies that when the prior belief of the vaccine $(\mu_\theta)$ is more inferior to the default value $(\overline{v})$ or when the agent has relatively accurate prior beliefs (higher

[11]Note that $\mathbb{E}[\theta|s] = \frac{\sigma_s^2\mu_\theta + \sigma_\theta^2 s}{\sigma_s^2 + \sigma_\theta^2}$, which is a linear function in $s$.

$\gamma$), the agent is less willing to acquire the vaccine information. Intuitively, the results in Proposition 1.3.1 suggest that the agent is more willing to acquire the information which has higher likelihood to persuade her beliefs of the vaccine to *override* the default choice.

If we assume that the mean of the vaccine's prior belief is lower than the default value ($\overline{v} \geq \mu_\theta$), the first result in Proposition 1.3.1 holds without absolute values.[12] Then we can further claim that $V(\cdot)$ increases in $\mu_\theta$. That is, the better the DM believes the vaccine is, the more likely she will acquire the information about the vaccine.

### Change in Beliefs

Given information $s$, the mean of the posterior belief of $\theta$ is $\frac{\sigma_s^2\mu_\theta+\sigma_\theta^2 s}{\sigma_s^2+\sigma_\theta^2}$. Hence the change in beliefs is

$$\delta(s) = \mathbb{E}\left[\theta|s\right] - \mu_\theta = \frac{\sigma_\theta^2}{\sigma_s^2+\sigma_\theta^2}(s-\mu_\theta) = \frac{1}{1+\gamma}(s-\mu_\theta).$$

Therefore we have the following comparative statics.

**Proposition.** The change in beliefs $\delta(s) = \mathbb{E}\left[\theta|s\right] - \mu_\theta$ increases in $s-\mu_\theta$. Furthermore, the absolute change in beliefs $|\delta(s)|$ decreases in $\gamma$.

Intuitively, when the signal deviates more from the prior mean, or when the signal is relatively more informative, the DM's belief will be persuaded more.

We can further combine the two predictions to identify the endogeneity between the information acquisition and the persuasion. The demand of the information is mainly determined by (i) the distance between the outside option value and mean of the prior belief of the vaccine effectiveness and (ii) the relative accuracy of the information. Furthermore, the persuasiveness is determined by (i) the strength of the signal and (ii)

[12] Suppose $\overline{v} < \mu_\theta$. Then it is more natural for the DM to take the vaccine *before* the information acquisition, which implies that the default value should be determined by the belief of the vaccine effectiveness.

the relative accuracy of the information. As information acquisition and persuasiveness are both connected with the relative accuracy, we can predict the comparative statics between information acquisition and persuasiveness.

**Corollary 1.** Given the distance between the mean of the prior belief and the default value ($|\mu_\theta - \overline{v}|$), the disagreement between the signal and the prior mean ($s - \mu_\theta$), and the cost of the information, the persuasion $\delta(s) = \mathbb{E}[\theta|s] - \mu_\theta$ will be increasing in $V(\mu_\theta - \overline{v}, c, \cdot)$.

This result explains why people may be more persuaded by the preferred information. Since we control the distance from the prior belief to default value and the strength of the signal, the actual factor correlates the information acquisition and the persuasiveness is the accuracy of the signal. Then the result can be interpreted as follows: the DM chooses the information which she believes is more accurate; then when she updates from this more accurate information, she finds the information more convincing and thus is willing to adjust her belief more.

### 1.3.2 Multiple Vaccines

In our experiment, the subjects are presented the information and update their beliefs of five vaccines simultaneously. If the vaccine information is not independent across different vaccine brands, the information of vaccine brand $A$ *can* help the agent update her belief of another vaccine.

The basic decision structure is the same as the one-vaccine case, despite that the beliefs are extended to the case of five vaccines. We divide the vaccine effectiveness into two parts: the common factor among different vaccines, and the vaccine specific factor. Specifically, let $\theta_j = \overline{\theta} + \tilde{\theta}_j$, where $\overline{\theta} \sim N(\overline{\mu}, \overline{\sigma}_\theta^2)$ is the *common* belief of the vaccine effectiveness across brands, and $\tilde{\theta}_j \sim N(\tilde{\mu}_j, \tilde{\sigma}_j^2)$ is the *vaccine $j$ specific* belief of the effectiveness. Then we write

$$\theta_j \sim N(\mu_j, \sigma_j^2),$$

where $\mu_j = \overline{\mu} + \tilde{\mu}_j$. We formally state two more assumptions to capture the division.

**Assumption 1.** (1) The common factor is independent with the vaccine specific factor (or formally, $\tilde{\theta}_j \perp \overline{\theta}$).

(2) The vaccine specific factors are independent between any two distinct vaccines $j$ and $k$ (or formally, $\tilde{\theta}_j \perp \tilde{\theta}_k$ for any $j \neq k$.)

Notice that

$$\mathrm{Cov}\left(\theta_j, \theta_k\right) = \mathrm{Cov}\left(\overline{\theta} + \tilde{\theta}_j, \overline{\theta} + \tilde{\theta}_k\right) = \mathrm{Cov}\left(\overline{\theta}, \overline{\theta}\right) = \mathrm{Var}\left(\overline{\theta}\right) = \overline{\sigma}_\theta^2.$$

Intuitively, as the only factor that any two vaccines share is the common factor, the covariance between vaccines beliefs is the variance of the common factor.

Let $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_J)^T$. Then we can find $\theta$ follows multivariate normal distribution:

$$\boldsymbol{\theta} \sim N\left(\boldsymbol{\mu}, \boldsymbol{\Sigma}_{\boldsymbol{\theta}}\right),$$

where $\boldsymbol{\mu} = (\mu_1, \ldots, \mu_J)^T$, $\boldsymbol{\Sigma}_{\boldsymbol{\theta} jj} = \sigma_j^2$, and $\boldsymbol{\Sigma}_{\boldsymbol{\theta} jk} = \overline{\sigma}_\theta^2$ for every $j \neq k$.

The information of the vaccine $j$, $s_j$, is centered at $\theta_j$ with a normally distributed error term, $\varepsilon_j \sim N(0, \sigma_s^2)$,

$$s_j = \theta_j + \varepsilon_j.$$

We add two more assumptions on the information structure.

**Assumption 2.** (1) The disturbance in the information about two vaccines are independent (or formally, $\varepsilon_j \perp \varepsilon_k$ for every $j \neq k$.)

(2) The disturbance in the information is independent with the effectiveness of the vaccines (or formally, $\varepsilon_j \perp \boldsymbol{\theta}$.)

Intuitively, we assume that the disturbances from the signal (for example, the errors from the laboratory trials) do not relate to the effectiveness of the vaccine itself, and they are independent among different vaccine brands. The two assumption imply that $\mathrm{Var}\left(s_j|\boldsymbol{\theta}\right) = \mathrm{Var}\left(\varepsilon_j\right) = \sigma_s^2$ for every $j$. Then we can determine the conditional distribution of $\boldsymbol{s} = (s_1, \ldots, s_J)^T$,

$$\boldsymbol{s}|\boldsymbol{\theta} \sim N(\boldsymbol{\theta}, \boldsymbol{\Sigma_s}),$$

where $\boldsymbol{\Sigma_s} = \sigma_s^2 \boldsymbol{I}_J$.

Let $D_j \in \{0, 1\}$ be the decision of whether to acquire the information of vaccine $j$ ($D_j = 1$ means the vaccine information is received, and $D_j = 0$ means the opposite), and $\boldsymbol{D} = (D_1, \ldots, D_J)^T$. We define $\boldsymbol{s}^* = (D_1 s_1, \ldots, D_J s_J)^T$, and $\boldsymbol{\Omega}_{\boldsymbol{s}}^* = \frac{1}{\sigma_s^2}(\boldsymbol{D}\boldsymbol{D}^T)$. Intuitively, we assign the deterministic value 0 to the vaccines that the agent does *not* receive. The corresponding distribution, $\boldsymbol{s}^*$, follows a *degenerate multivariate normal distribution*,

$$\boldsymbol{s}^*|\boldsymbol{\theta} \sim N(\theta, \boldsymbol{\Omega}).$$

Then the Bayesian posterior of $\boldsymbol{\theta}$ given $\boldsymbol{s}^*$ obeys the following distribution,

$$\boldsymbol{\theta}|\boldsymbol{s}^* \sim N\left(\left(\boldsymbol{\Omega} + \boldsymbol{\Sigma}_{\boldsymbol{\theta}}^{-1}\right)^{-1} \left(\boldsymbol{s}^T\boldsymbol{\Omega} + \boldsymbol{\mu}^T\boldsymbol{\Sigma}_{\boldsymbol{\theta}}^{-1}\right)^T, \left(\boldsymbol{\Omega} + \boldsymbol{\Sigma}_{\boldsymbol{\theta}}^{-1}\right)^{-1}\right).$$

The decision environment is the similar to the single vaccine case. Let $\overline{v}$ be the reservation value without any vaccine. Given the information, the agent compares the vaccine with the highest posterior mean with the reservation value. Denote $(\hat{\mu}_1|\mathbf{s}^*, \ldots, \hat{\mu}_J|\mathbf{s}^*) \equiv \mathbb{E}\left[\boldsymbol{\theta}|\boldsymbol{s}^*\right]$, and $\hat{\mu}^*|\mathbf{s}^* = \max_{j\in\{1,\ldots,J\}} \hat{\mu}_j|\mathbf{s}^*$. That is, $\hat{\mu}^*|\mathbf{s}^*$ is the effectiveness of the best vaccine given the information received. Call $j^*$ the best vaccine. Then the agent chooses vaccine $j^*$ if $\hat{\mu}^*|\mathbf{s}^* \geq \overline{v}$ and stay at the reservation value otherwise, and the value function becomes

$$v(\mathbf{s}^*) = \begin{cases} \hat{\mu}^*|\mathbf{s}^* & \text{if } \hat{\mu}^*|\mathbf{s}^* \geq \overline{v} \\ \overline{v} & \text{if } \hat{\mu}^*|\mathbf{s}^* < \overline{v} \end{cases}. \tag{1.2}$$

Hence, we can follow the same setting in Section 1.3.1 and calculate the value of information. The DM acquire the information if

$$\mathbb{E}_{\boldsymbol{s}}\left[v(\boldsymbol{s}^*)\right] - C(\boldsymbol{D}) \geq \overline{v},$$

where $C(\cdot)$ is the cost function of acquiring information. For simplicity, we assume the cost of acquiring the information about each brand of vaccine to be a constant $c$, so the total cost of acquiring information about $n$ vaccines becomes $nc$.

In the following subsection, we provide an example of two vaccines.

#### An Example of Two Vaccines

Following the settings, we list the environment of the two-vaccine case as the following assumptions.

**Assumption 3.** Let the effectiveness of vaccine 1 be $\theta_1 = \overline{\theta} + \tilde{\theta}_1$ and the effectiveness of vaccine 2 be $\theta_2 = \overline{\theta} + \tilde{\theta}_2$, where $\overline{\theta} \sim N(\overline{\mu}, \overline{\sigma}_\theta^2)$, $\tilde{\theta}_j \sim N(\tilde{\mu}_j, \tilde{\sigma}_j^2)$, $\tilde{\theta}_j \perp \overline{\theta}$, and $\tilde{\theta}_1 \perp \tilde{\theta}_2$. Denote $\mu_j = \overline{\mu} + \tilde{\mu}_j$ and $\sigma_j^2 = \overline{\sigma}_\theta^2 + \tilde{\sigma}_j^2$. Thus $\boldsymbol{\theta} = (\theta_1, \theta_2)$ follows a bivariate normal distribution,

$$\boldsymbol{\theta} \sim N\left( \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \overline{\sigma}_\theta^2 \\ \overline{\sigma}_\theta^2 & \sigma_2^2 \end{bmatrix} \right).$$

**Assumption 4.** The information that the DM receives for the vaccines are $s_1 = \theta_1 + \varepsilon_1$ and $s_2 = \theta_2 + \varepsilon_2$, where $\varepsilon_j \sim N(0, \sigma_s^2)$, $\varepsilon_1 \perp \varepsilon_2$, and $\varepsilon_j \perp \boldsymbol{\theta}$.

Given the cases that the DM receives only $s_1$, only $s_2$, or both $s_1$ and $s_2$, the means of the Bayesian posteriors are jointly normally distributed.

**Lemma.** *Given Assumptions 3 and 4, the mean of the posterior beliefs given receiving the signal sets $\{s_1\}$, $\{s_2\}$, and $\{s_1, s_2\}$ are respectively*

$$\mathbb{E}\left[\boldsymbol{\theta}|s_1\right] = \begin{bmatrix} \mu_1 + \frac{\sigma_1^2}{\sigma_s^2+\sigma_1^2}(s_1 - \mu_1) \\ \mu_2 + \frac{\overline{\sigma}_\theta^2}{\sigma_s^2+\sigma_1^2}(s_1 - \mu_1) \end{bmatrix}.$$

$$\mathbb{E}\left[\boldsymbol{\theta}|s_2\right] = \begin{bmatrix} \mu_1 + \frac{\overline{\sigma}_\theta^2}{\sigma_s^2+\sigma_2^2}(s_2 - \mu_2) \\ \mu_2 + \frac{\sigma_2^2}{\sigma_s^2+\sigma_2^2}(s_2 - \mu_2) \end{bmatrix}.$$

$$\mathbb{E}\left[\boldsymbol{\theta}|s_1, s_2\right] = \begin{bmatrix} \mu_1 + \frac{\sigma_1^2}{\sigma_s^2+\sigma_1^2+\sigma_2^2}(s_1 - \mu_1) + \frac{\overline{\sigma}_\theta^2}{\sigma_s^2+\sigma_1^2+\sigma_2^2}(s_2 - \mu_2) + \frac{\sigma_1^2\sigma_2^2-(\overline{\sigma}_\theta^2)^2}{\sigma_s^2(\sigma_s^2+\sigma_1^2+\sigma_2^2)}s_1 \\ \mu_2 + \frac{\overline{\sigma}_\theta^2}{\sigma_s^2+\sigma_1^2+\sigma_2^2}(s_1 - \mu_1) + \frac{\sigma_2^2}{\sigma_s^2+\sigma_1^2+\sigma_2^2}(s_2 - \mu_2) + \frac{\sigma_1^2\sigma_2^2-(\overline{\sigma}_\theta^2)^2}{\sigma_s^2(\sigma_s^2+\sigma_1^2+\sigma_2^2)}s_2 \end{bmatrix}.$$

When the information about the vaccine 1 only is received, the update in the mean of the belief of vaccine 1 effectiveness is determined by the weighted difference between the information ($s_1$) and the mean of vaccine 1's prior belief ($\mu_1$), where when the signal is relatively more accurate ($\sigma_s^2$ higher or $\sigma_1$ lower), the magnitude of the belief update is larger. This prediction is identical with the single vaccine version. Furthermore, the update in the mean of the belief of vaccine 2 effectiveness is also determined by the weighted difference between the information and the mean of vaccine 1's prior belief, while the weight is lower than the effect of the information on vaccine 1 ($\overline{\sigma}_\theta^2 \leq \sigma_1^2$). Intuitively, the information about vaccine 1 only helps the inference of the common factor between vaccine 1 and vaccine 2, so the magnitude of the update is.

When the DM receives the information about both vaccines, the posterior is determined by the weighted difference between the prior means of the vaccines and the information. For each of the vaccines, there is an additional (positive) term on the signal, representing the adjustment from iterated updating process.

With the posterior belief given the signal realization, the DM can decide whether to take one of the two vaccines or not taking anyone by comparing the mean of the posterior beliefs with the reservation value $\overline{v}$. If the mean of either of the vaccines exceeds $\overline{v}$, then the DM takes the one has the higher mean; if the means of both of the vaccines do not exceed $\overline{v}$, then the DM does not take any vaccine and take $\overline{v}$.

For each of the three possible information combinations, there are thresholds for the realized signals.

**Lemma.** *Suppose that* $\overline{v} \geq \mu_1 \geq \mu_2$.

*(a) When only* $s_i$ *is received: DM chooses vaccine* $i$ *if* $s_i \geq s_i^*$ *and receives the value of* $\mathbb{E}\left[\theta_i | s_i\right]$, *where*

$$s_i^* = \mu_i + \frac{\sigma_i^2 + \sigma_s^2}{\sigma_i^2} \left(\overline{v} - \mu_i\right).$$

*Otherwise, the DM rejects both of the vaccines and receives the value of* $\overline{v}$.

*(b) When* $s_1, s_2$ *are both received: DM chooses vaccine* $i$ *against vaccine* $j$ *if*

*(i)* $(\mu_i - \mu_j) + \frac{\sigma_i^2 - \overline{\sigma}_\theta^2}{\sigma_s^2+\sigma_1^2+\sigma_2^2}(s_i - \mu_i) - \frac{\sigma_j^2 - \overline{\sigma}_\theta^2}{\sigma_s^2+\sigma_1^2+\sigma_2^2}(s_j - \mu_j) + \frac{\sigma_1^2\sigma_2^2 - (\overline{\sigma}_\theta^2)^2}{\sigma_s^2(\sigma_s^2+\sigma_1^2+\sigma_2^2)}(s_i - s_j) \geq 0$

*(ii)* $\mu_i + \frac{\sigma_i^2}{\sigma_s^2+\sigma_1^2+\sigma_2^2}(s_i - \mu_i) + \frac{\overline{\sigma}_\theta^2}{\sigma_s^2+\sigma_1^2+\sigma_2^2}(s_j - \mu_j) + \frac{\sigma_1^2\sigma_2^2 - (\overline{\sigma}_\theta^2)^2}{\sigma_s^2(\sigma_s^2+\sigma_1^2+\sigma_2^2)} s_i \geq \overline{v}$,

*and the DM the value of* $\mathbb{E}\left[\theta_i | s_1, s_2\right]$. *Otherwise, the DM rejects both vaccines and receives the value of* $\overline{v}$.

When the DM receives only the information about one vaccines, the decision problem degenerates to the case where only the information about one vaccine is available. When the DM receives the information about both vaccines, the decision depends on two criteria: (1) which of the two vaccines has higher posterior mean, and (2) whether the mean of this better vaccine excess the default value $\overline{v}$.

The *ex-post* utility level given the information can then be derived from Lemma 1.3.2, which we denote as $v_1(s_1)$, $v_2(s_2)$, or $v_{1,2}(s_1, s_2)$ given different bundles of information acquired. The DM can then choose either to acquire only the information about vaccine 1, only about vaccine 2, or acquire the information about both vaccines. The DM first finds the expected value given the signal combinations, and the she chooses the optimal information bundle.

We denote the following value functions:

$$V_1(\mu_1, \mu_2, \overline{v}, \sigma_1^2, \sigma_2^2, \overline{\sigma}_\theta^2, \sigma_s^2, c) = \mathbb{E}_{s_1}\left[\mathbb{E}\left[v_1(s_1)|s_1\right]\right] - c$$

$$V_2(\mu_1, \mu_2, \overline{v}, \sigma_1^2, \sigma_2^2, \overline{\sigma}_\theta^2, \sigma_s^2, c) = \mathbb{E}_{s_2}\left[\mathbb{E}\left[v_2(s_2)|s_2\right]\right] - c$$

$$V_{1,2}(\mu_1, \mu_2, \overline{v}, \sigma_1^2, \sigma_2^2, \overline{\sigma}_\theta^2, \sigma_s^2, c) = \mathbb{E}_{s_1,s_2}\left[\mathbb{E}\left[v_{1,2}(s_1, s_2)|s_1\right]\right] - 2c$$

Note that the cost of the information bundle of both vaccines is $2c$.

The following table displays the decision rule given the parameters.

| | Which of the following is the largest? | | | |
|---|---|---|---|---|
| the largest: | $V_1(\cdot)$ | $V_2(\cdot)$ | $V_{1,2}(\cdot)$ | $\overline{v}$ |
| then acquire: | $s_1$ | $s_2$ | $s_1$ and $s_2$ | no info |

Then we can give the following similar prediction as in Section 1.3.1.

**Proposition.** Suppose $\max\{\mu_1, \mu_2\} \le \overline{v}$. Then $V_1$, $V_2$, and $V_{1,2}$

(i) increase in $\mu_1$ and $\mu_2$,

(ii) decrease in $\sigma_1^2$, $\sigma_2^2$, and $\sigma_\theta^2$,

(iii) increase in $\sigma_s^2$.

## 1.4 Sample Description

### 1.4.1 Beliefs about the Vaccine effectiveness

The subjects stated their beliefs about vaccine effectiveness. Specifically, we asked subjects to provide their assessments of beliefs on the four factors: efficacy, hospitalization prevention rate, adverse event rate, and severe adverse event rate.[13] The subjects stated their beliefs before and after the treatment phase. For each of the five vaccines listed, the subjects had to state their beliefs of four effectiveness factors, so each factor has five observations (one per vaccine) for each subject.

Table 1.1 summarizes the beliefs and changes before and after the information exposure. The first two rows show the average beliefs on each factor of vaccine effectiveness before and after the treatments. Though not significant, the average belief in vaccine effectiveness increases after the treatment phase (higher efficacy/hospitalization prevention rate and lower adverse event rates).

Figure 1.5 shows the distribution of each factor's beliefs before and after the treatment. Over half of the observations have a belief of at least 70% on efficacy and at least 80% on hospitalization prevention rate, and half of the observations have a belief of at most 20% chance that the vaccine can cause severe adverse events. We can also see that the distribution of beliefs about efficacy and hospitalization prevention rates moves right, while the distribution of beliefs about adverse event rates moves left. This indicates that our subjects' beliefs generally become more optimistic after the intervention.

[13] All factors range from 0% to 100%. The subjects were told how these factors are calculated.

We further summarize the belief observation level changes in beliefs before and after the information treatments in the third and fourth rows of Table 1.1. On average, the subjects hold more positive beliefs about the vaccines' effectiveness after receiving the information. The last two rows are the gap between the beliefs and the information we provide. Overall, our subjects undervalue the vaccines compared to what the scientific reports suggest, as the gaps are negative in efficacy and hospitalization prevention rates and are positive in adverse event rates.

Table 1.1: Summary of the Belief Changes

| | Efficacy | Hospitalization | Adverse Event | Severe AE |
|---|---|---|---|---|
| Pre-treatment Beliefs | 69.00 | 71.00 | 60.76 | 32.76 |
| | (21.33) | (24.05) | (27.26) | (29.33) |
| Post-treatment Beliefs | 72.10 | 75.78 | 52.60 | 29.16 |
| | (23.26) | (25.26) | (29.30) | (30.40) |
| Adjustment in Beliefs (Post − Pre) | 3.100 | 4.780 | -8.161 | -3.601 |
| | (16.63) | (21.77) | (29.00) | (24.18) |
| \| Adjustment in Beliefs \| | 11.41 | 14.63 | 21.34 | 15.45 |
| | (12.49) | (16.81) | (21.27) | (18.94) |
| Pre-treatment Belief − Information | -12.98 | -25.40 | 15.46 | 32.02 |
| | (22.45) | (25.05) | (35.85) | (29.34) |
| \| Pre-treatment Belief − Information \| | 18.61 | 26.25 | 32.27 | 32.07 |
| | (18.05) | (24.16) | (21.98) | (29.28) |

*Notes.* Standard deviations in the parentheses. The information variable is the statistic on the page of vaccine information. The unit of the beliefs and the information is percentage (0–100). The statistics in this table include only data from the three main treatments. The information for Adverse Event and Severe Adverse Events is based on the statistics of the treatment group in the report.

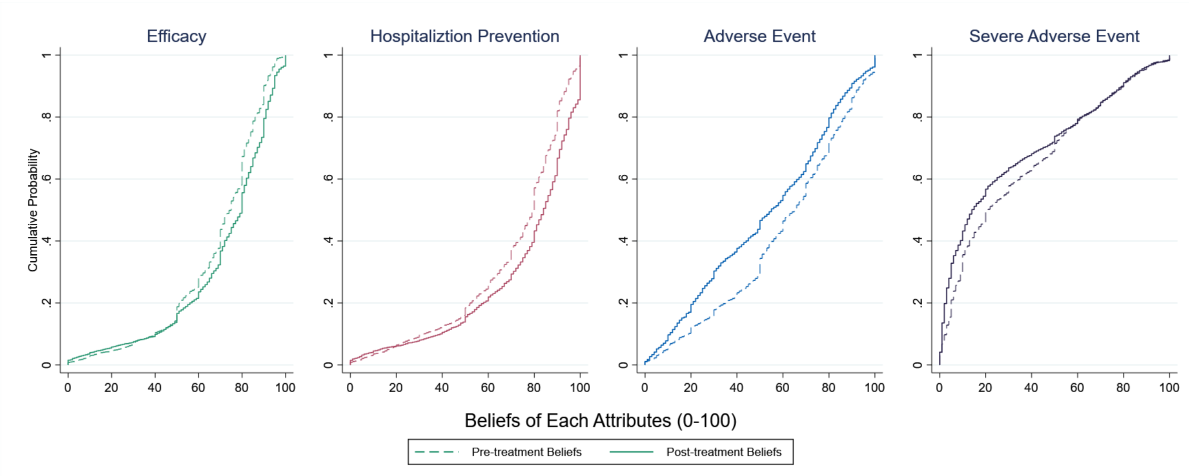



Figure 1.5: Distribution of Pre-treatment and Post-treatment Beliefs

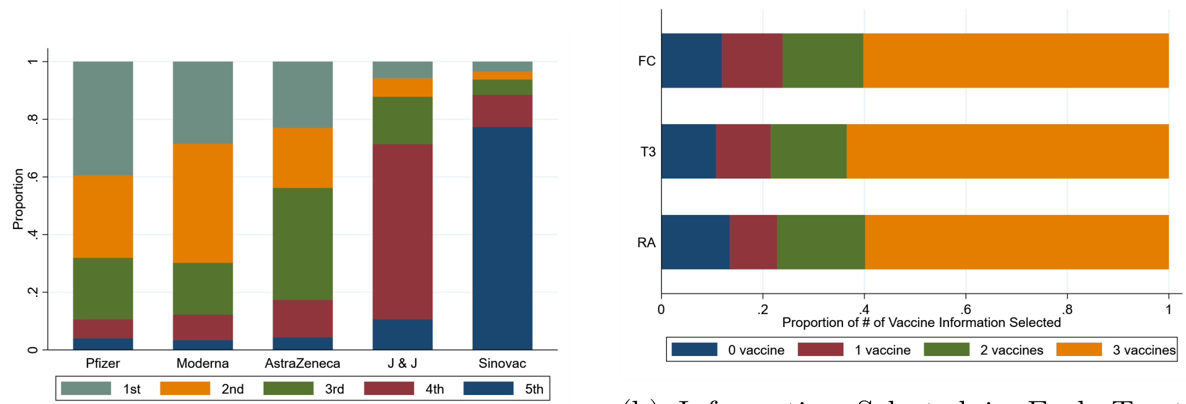
*Notes.* The dashed lines represent the distribution of beliefs before the treatment. The solid lines represent the distribution of beliefs after the treatment.

### 1.4.2 The Subjects' Demand for the Vaccine Effectiveness Information

Figure 1.6 depicts the subjects' responses to the two questions. As vaccines from Pfizer, Moderna, and AstraZeneca are the only available vaccines in Taiwan at the moment, the information about the three vaccines was also more popular among the subjects. For the number of vaccines selected, around 60% of the subjects selected information about three vaccines (the maximum number they can select). There is no significant difference in information demand among the treatments.

### 1.4.3 Preference on Receiving Vaccines

The subjects also stated their willingness to receive vaccines. Two questions were used to evaluate their preferences. The first one is a direct question asking how much they preferred each vaccine, with a 0-100 scale. The second question is how long the subjects would be willing to wait to receive the vaccine. As the vaccines were not fully




(a) Vaccine Information Ranking

(b) Information Selected in Each Treatment

Figure 1.6: Vaccine Information Demands

*Notes.* Panel (a) shows the ranking distribution for each vaccine. Panel (b) shows the number of vaccines selected in the "Number" question in each treatment arm.

accessible in Taiwan when we conducted the experiment, this question provides a more succinct scheme to evaluate the subjects' preferences. Similarly, the questions were asked before and after the treatment phase, right after the beliefs were elicited.

### 1.4.4 Familiarity with the Vaccines and the Receptions

To control the subjects' knowledge about the vaccines before they received the information, we asked them to judge how familiar they thought they were with the vaccines. We also included quiz questions about the facts about the vaccines to objectively measure the subjects' familiarity with the vaccines.[14] In general, the subjects are more familiar with the vaccines available in Taiwan. We also find that the quiz correctness and the subjects' subjective familiarity with the vaccines are positively correlated.

The subjects also reported their reception of the vaccines. For each vaccine, we asked the subjects whether they had received or registered for the vaccine (at least one dose).

[14] The quiz questions are about (1) the technique platform applied by each vaccine and (2) the recommended number of doses.

The summary statistics are in Appendix Table C4.

In our sample, 87% of the subjects have received at least one vaccine shot. At the time of the experiment, there were around 70% of the population in Taiwan had received their first vaccine shot, and around 45% had received the second shot. Since there were still some people considering which vaccine to take as the second shot, our information treatment can impact people's vaccine choices. In addition, the comparison between different vaccines was a popular topic among the public, while the public information was not as transparent as in our setting. This gives us a good environment to study information consumption and belief updates.

### 1.4.5 Information Engagement

We also collect each subject's interaction data with the information. Specifically, we detect whether the subjects clicked the "bottoms" on the information page (as shown in Figure 1.3) and the time spent on the information page. We summarize subjects' interactions with the information in Table B3. First of all, our subjects are very willing to engage with the information. For each of the attributes, approximately 80% of the observations have clicked the bottom and checked the information at least once, and the median time spent on a page is 37.44 seconds. Moreover, we observe that the subjects are more willing to check the information that they are more interested in, which provides secondary evidence that justifies our elicitation of the preferences of the information.

## 1.5 Results

In this section, we document the empirical results we find in our experiment. Following the theory framework, we will discuss our experiment results in the three main aspects. First, we investigate how the subjects' beliefs about the vaccine's effectiveness influence their selection of vaccine information. Second, we investigate how the persuasiveness of the information interacts with our subjects' information demand. Lastly, we verify whether the update in beliefs transmits to the preference for vaccines.

### 1.5.1 Information Selection

We first look at factors that affect the subjects' information selections. As elaborated in Proposition 1, the subjects should be more willing to select the information if they expect the information will yield a higher posterior belief. In addition, they should be more willing to select the information if the its relative accuracy (comparing to the prior belief) is higher, as it reduces more uncertainty. To capture the subjects' belief about the relative accuracy, we use subjects' self-evaluated familiarity of the vaccines as a proxy;[15] the less familiar they are with a vaccine, the more uncertainty the information can reduce. Therefore, we can test the following prediction.

**Prediction.** The subjects are more willing to receive the information about the vaccines (1) they believe are better, and (2) they are less familiar about.

Figure 1.7(a) depicts the stated belief of each vaccine in each of the four factors. The left panel sorts the stated beliefs by the willingness to read elicited from the information ranking question. We can see that for the vaccines the subjects are more interested in knowing the information (more willing to read), and the stated beliefs in efficacy and hospitalization prevention rate are higher. The right panel categorizes the vaccines with both of the information demand questions; if the vaccine information is selected by a subject to read, the vaccine will be categorized as "Selected Top 3"; if the vaccine

[15] We admit that the familiarity may not be a perfect proxy of the variances of subjects' beliefs. As a robustness check, we also examined the subjects' knowledge about the vaccines with quizzes. The subjects answer more quiz questions correctly for the vaccines they claim are more familiar with. We provide a short discussion in Section 1.6.

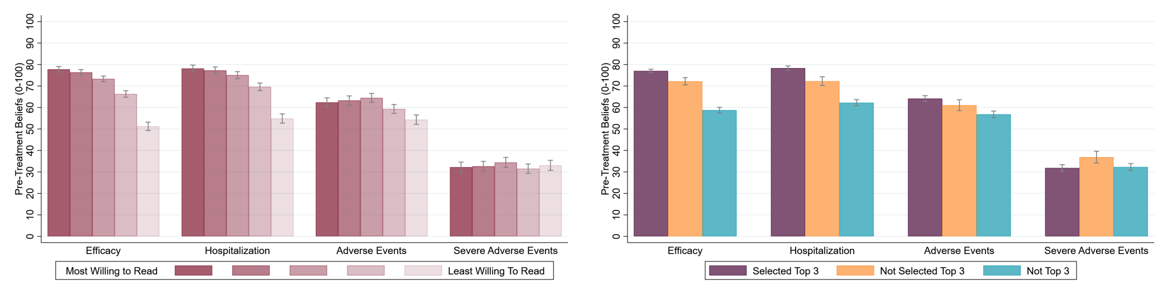
information is not selected but still ranked as top 3 by a subject, the vaccine will be categorized as “Not Selected Top 3”; if the vaccine information is not ranked as top 3 by a subject, the vaccine will be categorized as “Not Top 3”. We can also see that for the selected vaccines, the stated pre-treatment beliefs in efficacy and hospitalization prevention rates are higher as well. We note that these patterns do not appear for adverse events.

To evaluate the theory prediction, we assume the default value to be the highest stated belief among the five vaccines in each of the factors.[16] Figure 1.7(b) depicts the gap between the stated belief of each vaccine and the default value in each of the four factors. The results are similar to panel (a), where the more interested vaccines are closer to the best vaccines (in efficacy and hospitalization prevention rates.) These finding about vaccine effectiveness coheres with the rational information acquisition framework that people are more interested in the information that has a higher chance of yielding a better decision (in this case, receiving better vaccines).

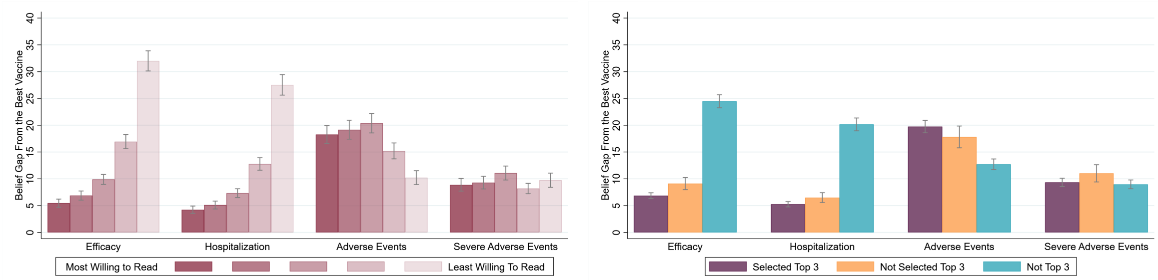
Figure 1.7(c) shows the correlation between the subjects' vaccine familiarity and the vaccine demand. Contrary to the theory prediction, the vaccines that the subjects select or are more willing to read are the vaccines that the subjects are *more* familiar with. Although the difference is relatively minor (within the range of 4-5 among the top 3 vaccines), this phenomenon implies a sub-optimality of their information selection. We will discuss the possible mechanisms that could cause this tendency to choose familiar information later in this subsection.

We estimate the following regression models to quantitatively examine the prediction

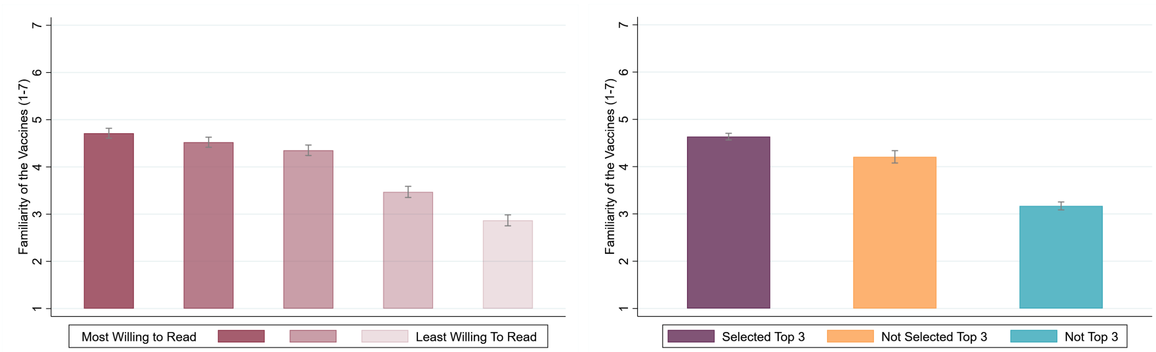
[16] The default value is unobserved under our setting. We assume the default value could be higher or equal to the highest stated belief among the five vaccines, but not lower; if the unobserved default value is lower than any of the five vaccines' stated beliefs, the agent should take the vaccine whose performance exceeds the default value, so the default option should switch to the best vaccine at the time.




(a) Beliefs of effectiveness by willingness to read (left) and information preference (right)




(b) Gap between beliefs and default by willingness to read (left) and information preference (right)




(c) Vaccine familiarity by willingness to read (left) and information preference (right)

Figure 1.7: Information Preference in Vaccine Effectiveness and Familiarity

*Notes.* The ranks in the willingness to read panels are determined by the question "*Please rank the following vaccines from the highest to the lowest based on how much you want to read the information about the vaccine.*" For each of the factors in (b), the distance of beliefs from the best vaccine for some factor is defined as the difference between the belief in that factor of the vaccine and the highest belief in that factor among all vaccines. 95% confidence intervals of the means of each bar are included.

and the findings from Figure 1.7.

$$\text{InfoDemand}_{i,v} = \alpha + \sum_k \beta_k \text{Pre-beliefRank}^k_{i,v} + \lambda \text{Familiarity}_{i,v} + X_i \xi \tag{1.3}$$

$$\text{InfoDemand}_{i,v} = \alpha + \sum_k \gamma_k (\text{Default}^k_i - \text{Pre-belief}^k_{i,v}) + \lambda \text{Familiarity}_{i,v} + X_i \xi \tag{1.4}$$

The dependent variables are the indexes of *information demand*. We use two variables from the two questions eliciting the information demands. The first one is the vaccine information ranking that the subjects stated, where 1 means the least interested, and 5 means the most interested. The second one is the binary variable of whether the subjects select the information about the vaccines. There are two sets of main explanatory variables; each includes four variables about the effectiveness factors. The first set is the pre-treatment belief rankings among the five vaccines, where 1 means the subject believes the vaccine is the worst-performing vaccine in that factor, and 5 means the vaccine is the best-performing vaccine in that factor. The second set is the belief gap from the default value as defined in Figure 1.7, where we assume the default value to be the highest stated belief among the five vaccines. In addition, we include the variable of vaccine familiarity.

Table 1.2 summarizes the estimation of the above regressions, which suggests similar findings. From columns (1) and (3) in Table 1.2, we can see that when the subjects believe the vaccine is better (especially in efficacy and hospitalization prevention rate), the subjects will rank the information about that vaccine higher, and they will be more likely to select the information. Columns (2) and (4) give a similar observation—the further the gaps from the vaccine with the highest efficacy or hospitalization rate are, the less preferred the information is.

In all of the columns, we find our subjects are more willing to read the information that they *are* familiar with. To explain the sub-optimality of the information selection, we

Table 1.2: Information Preference and Selection

| | *Dependent Variables* | | | |
|---|---|---|---|---|
| | Info Rank | | Selected | |
| | (1) | (2) | (3) | (4) |
| *Explanatory Variables* | Belief Ranking | Gap from Highest | Belief Ranking | Gap from Highest |
| Efficacy | 0.29*** | -0.02*** | 7.20*** | -0.63*** |
| | (0.02) | (0.00) | (0.75) | (0.07) |
| Hospitalization Prevention | 0.17*** | -0.01*** | 4.47*** | -0.15* |
| | (0.02) | (0.00) | (0.78) | (0.07) |
| Adverse Events | 0.04* | 0.00** | 2.27*** | 0.14** |
| | (0.02) | (0.00) | (0.64) | (0.05) |
| Severe Adverse Events | 0.01 | 0.00* | -0.03 | 0.01 |
| | (0.02) | (0.00) | (0.60) | (0.07) |
| Familiarity | 0.21*** | 0.25*** | 7.29*** | 8.36*** |
| | (0.01) | (0.01) | (0.60) | (0.62) |
| Constants | 0.57*** | 2.52*** | -32.01*** | 17.73*** |
| | (0.09) | (0.08) | (4.70) | (4.62) |
| Observations | 3145 | 3145 | 3145 | 3145 |
| Subjects | 632 | 632 | 632 | 632 |
| $R^2$ | 0.36 | 0.32 | 0.24 | 0.21 |
| Mean of Dep. Variable | 3 | 3 | 45.2 | 45.2 |

*Notes.* Clustered (at subject level) standard errors in parentheses. The subjects' family income, college majors, and sex are controlled. The coefficients and the mean of the dependent variable in (3) and (4) are in percentage. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ .

introduce two possible mechanisms. First, people may not be interested in knowing more about the vaccines that they have no access to, which they naturally are not familiar with. To resolve this concern, we look at only the observations about the available vaccines in Taiwan at the moment (AstraZeneca, Pfizer, and Moderna). The results are shown in Table C5, where we still find a positive correlation between information selection and familiarity. Second, people may seek the information to justify their past choices, which they are also more familiar with. If so, the selection of the more familiar vaccines could only reflect the self-justification behavior, and adding the vaccine reception record into the regression specification can dilute the effects of familiarity. Thus, we estimate the specification including both vaccine reception history and familiarity to address this concern, where the results are presented in Table C6. We find that the coefficients of familiarity do not qualitatively change compared to the baseline results, and the preference for information is positively correlated with the vaccine reception history. The results do not support the possibility that the preference for information about the more familiar vaccines solely comes from the vaccine reception before. Therefore, we conclude that the subjects tend to choose information about more familiar objects, which is sub-optimal.

**Result 1** (Information Selection)**.**

- ***Align with the prediction****: People select the information about the vaccines they believe are more effective.*
- ***Disagree with the prediction****: People select the information about the vaccines they are more familiar about.*

### 1.5.2 Belief Updates

In this subsection, we discuss how much the subjects' beliefs are persuaded by the information. Specifically, we look at how much the subjects adjusted their beliefs before and after they received the information at the individual level.

Figure 1.8 depicts belief changes before and after the information exposure stage in each of the factors. The observations are categorized into three groups same as in Figure 1.7, where we further divided each category by whether the subject receives the information in the exposure stage.

First of all, the mean belief adjustments are mostly positive in efficacy and hospitalization prevention rates and are mostly negative in adverse event rates. In other words, after reading the information provided, the subjects on average become more optimistic about the vaccines. If we compare the sizes of the belief adjustments for observations that the information is received between categories, the adjustment in *Selected Top 3* group is slightly higher than in *Not Selected Top 3*, while the difference in belief adjustment between the *Selected Top 3* and *Not Top 3* group is not significant.

Another finding is about the adjustments for the vaccines that the subjects *did not* receive any information from the treatment. Ideally, if a subject does not receive any new information, he should not have any update on the specific vaccine; in other words, the average change in beliefs should be around zero. However, when we look at the observations that the subject did not receive any information about, it is only the case for the *Not Top 3* category, while there are still some updates in the *Top 3* categories. This indicates that there may be some "leakage" from the information received.

In the rest of the subsection, we discuss two cases of the belief updates from the information. We first discuss the direct update that the subjects receive the information about the vaccine, then we discuss the indirect update that the subjects *do not* receive the

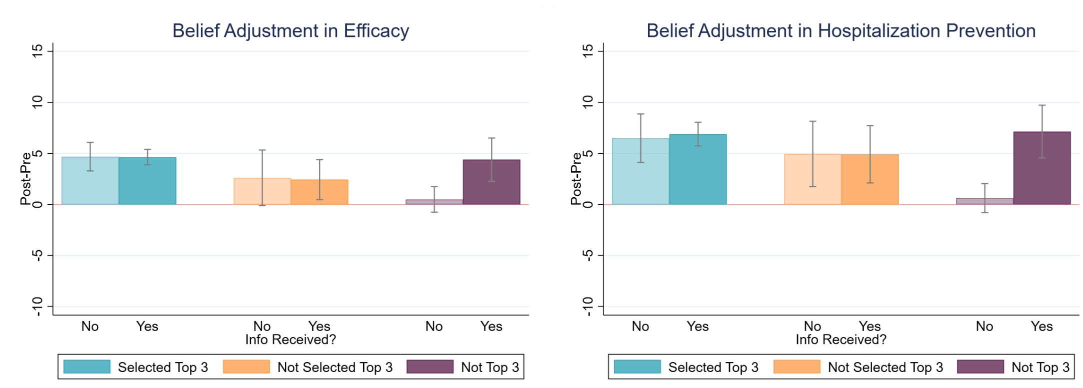



Figure 1.8: Changes in Beliefs

*Notes.* The mean of the changes in beliefs before and after the information exposure stage are depicted. The change is defined by Post-treatment belief − Pre-treatment belief. Within each category, the left/lighter bar is for the observations that the subjects do not receive the vaccine information, and the right/deeper bar is for the observations that the subjects receive the information. 95% confidence intervals of the means are plotted for each category.

information about the vaccines, which implies the information leakage between vaccines.

### Direct Update

As elaborated in Section 1.5.1, the pre-treatment beliefs can be correlated with the information demand. To estimate the correlation between the belief adjustment and information selection, we can derive a prediction from Corollary 1.

**Prediction.** Define the *persuasion* as the belief movement before and after the treatment $(\mathbb{E}[\theta|s] - \mu_\theta)$. Then

(i) the persuasion increases in the disagreement between the information and the prior belief $(s - \mu_\theta)$,

(ii) the persuasion decreases in familiarity, and

(iii) controlling (1) the gap between the default value and the pre-treatment belief and (2) the disagreement between the information and the prior belief, the belief adjustment will be larger if the received information is selected.

The disagreement between the information and the prior belief is defined as the difference between the signal that the subject sees and the subject's pre-treatment belief ($s - \mu_\theta$). The more disagreed the information and the belief is, the more "surprising" the information is to the subject. The last prediction is adapted from Corollary 1. The intuition is that the information people *select* is about the vaccine people are less familiar with, so when people receive their selected information, they receive the less familiar information, from which people should update more. However, Result 1 implies the opposite that people select the information about the vaccines they are *more* familiar with. Therefore, Prediction 2-(iii) becomes uncertain *a priori*.

To examine the prediction, we will estimate the following regression:

$$\begin{aligned}\text{BeliefAdjustment}_{i,v} = \alpha &+ \beta_1 \text{SelectedTop3}_{i,v} + \beta_2 \text{NotSelectedTop3}_{i,v} + \delta \text{Disagreement}_{i,v} \\ &+ \lambda \text{Familiarity}_{i,v} + \sum_k \gamma_k (\text{Default}_i^k - \text{Pre-belief}_{i,v}^k) + X_i \xi \quad (1.5)\end{aligned}$$

The gap between the default value and the pre-treatment belief is identically defined as in (1.4). If Prediction 2 is true, we should see $\beta_1$ and $\beta_2$ to be positive and $\lambda$ to be negative. In addition, by Proposition 2, $\delta$ should be positive.

We will focus on the efficacy and hospitalization prevention rates in the regression specification.[17] Table 1.3 summarizes the estimation of equation (1.5), where we include the observations of the vaccines that the subjects receive the information about. Models (1) and (4) include only the signal disagreement ($s - \mu_\theta$) and familiarity. First, the belief change is positively correlated with signal strength, which suggests that the subjects are (on average) correctly using the information to update beliefs. Additionally, familiarity has either null or positive effects on updates, which implies that people update even *more*

[17]The information provided for the side effects includes statistics for both the control group and treatment group in the selected scientific reports, where the subjects may not take only one of them to update their beliefs. Please see the online appendix for the results with the same specifications.

when they see the information they are more familiar with.

However, this positive update can be coming from the fact that the information is selected by the subjects. Models (2) and (5) directly test this hypothesis. We find that people tend to update more when they receive and update according to the information they select. We further include the familiarity in (3) and (6) to estimate equation (1.5), and the upward updating from the information selected persists. We also note that for the vaccines the willingness to read is ranked in the top 3 but not selected, there is no upward updating significantly different than zero. Combining with the findings summarized in Result 1, we conclude that people are more persuaded by the information they select; although it satisfies the theory model prediction about information selection qualitatively, the mechanism is not fully rationalizable.

We discuss possible reasons for the sub-optimal use of the selected information. First, people may seek the endorsement for their past choices of vaccines. As we note from Table C6, people are also more interested in seeing the information about the vaccines they have received before. If the subjects select the information for endorsement, we should see a positive effect in the vaccine reception if we include it in the specifications in Table 1.3. The results are shown in Table C7. The coefficients of vaccine reception history are positive, and the coefficients of familiarity become insignificant, which aligns with our conjecture. However, the effects of the selected vaccines are still positive. Hence, the vaccine reception endorsement does not fully explain the positive effects of the selected vaccines.

The second mechanism is a version of motivated reasoning. If the rational information acquisition framework is true, the subjects expect that the information will (on average) make their belief of vaccine effectiveness more optimistic. Given this expectation, the subjects may be more sensitive to the information if the information tells something optimistic, that is, shows that the vaccine is more effective than their prior is. Hence, this

Table 1.3: Update in Beliefs (Direct)

| | *Belief Update*: Post-Treatment Belief − Pre-Treatment Belief | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Efficacy | | | Hospitalization | | |
| Signal Disagreement | $0.30^{***}$ | $0.27^{***}$ | $0.28^{***}$ | $0.52^{***}$ | $0.63^{***}$ | $0.64^{***}$ |
| | (0.03) | (0.03) | (0.03) | (0.04) | (0.05) | (0.05) |
| Familiarity | $0.58^{*}$ | | 0.25 | $1.58^{***}$ | | $0.95^{*}$ |
| | (0.29) | | (0.31) | (0.45) | | (0.44) |
| Selected Top 3 | | $3.05^{**}$ | $2.86^{*}$ | | $4.60^{**}$ | $3.86^{**}$ |
| | | (1.16) | (1.13) | | (1.43) | (1.42) |
| Not Selected Top 3 | | 0.21 | 0.30 | | 0.87 | 0.59 |
| | | (1.44) | (1.45) | | (1.74) | (1.75) |
| Constants | -1.73 | -1.22 | -2.27 | $-14.58^{***}$ | $-10.64^{**}$ | $-14.10^{***}$ |
| | (2.28) | (2.15) | (2.60) | (3.87) | (3.44) | (3.90) |
| Observations | 1754 | 1762 | 1754 | 1754 | 1762 | 1754 |
| Subjects | 611 | 611 | 611 | 611 | 611 | 611 |
| $R^2$ | 0.16 | 0.19 | 0.19 | 0.29 | 0.34 | 0.34 |
| Mean of Dep. Variable | 4.29 | 4.26 | 4.29 | 6.64 | 6.65 | 6.64 |
| Pre-treatment Beliefs Controlled? | No | Yes | Yes | No | Yes | Yes |

*Notes.* Clustered (at subject level) standard errors in parentheses. The subjects' family income, college majors, and sex are controlled in all models. Pre-treatment beliefs are controlled in models (2), (3), (5), and (6). $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ .

motivated reasoning can lead to asymmetric updates between subjects who underestimate or overestimate the effectiveness of the vaccines. We estimate the benchmark specifications in Table 1.3 with the two subgroups (under/overestimated) and show the results in Tables C8 and C9 respectively. For the underestimated group (the subjects see the information that is higher than their prior beliefs), the effects of the selected information still persist. However, for the overestimated group (the subjects see the information that is lower than their prior beliefs), the effects from the selected information become not significantly different from zero. This asymmetric updating pattern provides suggestive evidence that subjects have a pattern of motivated reasoning, which resonates with the information acquisition framework.

### Indirect Update

In reality as well as our experiment, it is possible that people *indirectly* update beliefs from other sources (*e.g.*, updating the beliefs about Pfizer when only Moderna information is available). In this part, we discuss the indirect update patterns in our experiment. To measure the indirect update, we include the signal strength of other vaccines in the remaining models. Specifically, it is defined by the mean of the "signal strength" variable over the other vaccines that the subject has received the information about.[18] We focus on how much subjects react to the indirect information. From Lemma 1.3.2, the indirect update should be smaller, as the indirect information carries only the common uncertainty among vaccines but does not reveal the vaccine-specific uncertainty. (For example, we can learn about the general effectiveness of the vaccines on the market from information about Pfizer, but we cannot learn the Moderna-specific effectiveness from

[18]For the specifications that include signal strength of other vaccines, the observations are dropped if there is no information about "other vaccines" received. Two possible cases are included: (1) the subject acquires information about zero vaccine and is assigned to the Full Compliance group, and (2) the subject acquires information about one vaccine and is assigned to the Full Compliance group while the observation is of the exact vaccine that she selects and receives the information.

it.)

We estimate an alternative version of Equation 1.5 and show the results in Table 1.4. Models (1) and (3) include the observations that the subjects do *not* receive direct information about the vaccines. We observe that the coefficients estimated from the indirect update (signal disagreement of other vaccines) are smaller than the direct update shown in Table 1.3. Furthermore, models (2) and (4) include the observation that the subjects receive *both* direct and indirect information. We find that when direct information is available, indirect information does not have significant effects on belief updates. The two observations also align with the theory framework qualitatively.

Table 1.4: Update in Beliefs (Indirect)

| | *Belief Update* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Efficacy | | Hospitalization | |
| Signal Disagreement | | $0.26^{***}$ | | $0.58^{***}$ |
| | | (0.03) | | (0.05) |
| Signal Disagreement of Other Vaccines | $0.13^{**}$ | 0.05 | $0.37^{***}$ | 0.05 |
| | (0.04) | (0.04) | (0.04) | (0.04) |
| Selected Top 3 | $5.77^{***}$ | $2.83^{*}$ | 1.95 | $4.36^{**}$ |
| | (1.09) | (1.16) | (1.53) | (1.43) |
| Not Selected Top 3 | -0.85 | -0.23 | 0.53 | 0.59 |
| | (2.30) | (1.44) | (2.41) | (1.76) |
| Constants | -2.95 | -1.77 | $-9.59^{**}$ | $-11.14^{**}$ |
| | (2.87) | (2.11) | (3.69) | (3.51) |
| Observations | 1209 | 1741 | 1209 | 1741 |
| Subjects | 590 | 590 | 590 | 590 |
| $R^2$ | 0.11 | 0.20 | 0.21 | 0.34 |
| Mean of Dep. Variable | 1.15 | 4.24 | 2.35 | 6.63 |
| Info Recevied? | No | Yes | No | Yes |

*Notes.* Clustered (at subject level) standard errors in parentheses. The subjects' family income, college majors, sex, and pre-treatment beliefs are controlled in all models. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ .

**Result 2** (Belief Update)**.**

- ***Align with the prediction***:
  - *People's belief update more from the information they select.*
  - *People's belief update more when the direct information is available.*
- ***Disagree with the prediction***:
  - *People do not update less when they see the information they are more familiar with.*

### 1.5.3 Preference Changes

The next question is whether the information changes people's preference and willingness to receive vaccine shots. In Table 1.5, we summarize the preference changes in each of the information demand groups. On average, the change in vaccine preferences increase by 0.03 out of 100 after the treatment phase (standard deviation 18.12), while the absolute change is 10.12 out of 100 (standard deviation 15.03). We also asked how many weeks the subjects were willing to wait to receive that specific vaccine. On average, the subjects are willing to wait 0.99 more weeks after the treatment phase (standard deviation 9.40), and the absolute difference is 4.74 weeks (standard deviation 8.17) on average. Nonetheless, we note that the change in weeks willing to wait is not prominent. 37.5% of the observations report the same numbers of weeks before and after the treatment phase, and 50.6% have the change less or equal to one week.

Table 1.5: The Preferences of Vaccines: By Treatments

| | Selected Top 3 | | Non-Selected Top 3 | | Not Top 3 | | |
|---|---|---|---|---|---|---|---|
| | Received | Not Received | Received | Not Received | Received | Not Received | Total |
| *Preference* | | | | | | | |
| Pre-treatment | 82.90 | 76.68 | 75.17 | 73.27 | 50.99 | 43.27 | 66.09 |
| | (21.56) | (25.41) | (25.49) | (28.50) | (36.36) | (35.50) | (33.78) |
| Post-treatment | 84.61 | 75.64 | 73.32 | 73.24 | 49.89 | 42.52 | 66.12 |
| | (22.18) | (27.65) | (27.76) | (29.48) | (37.77) | (36.13) | (35.09) |
| Post − Pre | 1.71 | -1.04 | -1.85 | -0.03 | -1.10 | -0.75 | 0.03 |
| | (15.06) | (17.49) | (20.32) | (16.89) | (22.21) | (19.52) | (18.12) |
| \| Post − Pre \| | 8.32 | 9.68 | 11.90 | 9.11 | 13.40 | 10.99 | 10.12 |
| | (12.67) | (14.59) | (16.56) | (14.21) | (17.73) | (16.15) | (15.03) |
| *Weeks Willing to Wait* | | | | | | | |
| Pre-treatment | 16.56 | 17.07 | 16.80 | 18.17 | 17.31 | 14.12 | 16.37 |
| | (14.79) | (15.53) | (15.49) | (15.95) | (15.77) | (13.72) | (14.96) |
| Post-treatment | 17.84 | 17.39 | 18.26 | 19.02 | 17.09 | 14.70 | 17.26 |
| | (15.43) | (15.88) | (16.59) | (15.30) | (15.69) | (14.09) | (15.40) |
| Post − Pre | 1.21 | 0.94 | 2.24 | 0.38 | -0.85 | -0.27 | 0.39 |
| | (11.81) | (10.20) | (15.72) | (13.58) | (14.12) | (14.98) | (13.06) |
| \| Post − Pre \| | 5.50 | 4.62 | 8.13 | 6.93 | 6.42 | 6.15 | 5.59 |
| | (10.52) | (9.14) | (13.64) | (11.67) | (12.60) | (13.67) | (11.81) |
| Never Take (Pre) (%) | 5.39 | 7.22 | 10.27 | 16.02 | 40.40 | 52.02 | 24.10 |
| | (22.59) | (25.93) | (30.41) | (36.77) | (49.14) | (49.99) | (42.77) |
| Never Take (Post) (%) | 5.39 | 9.03 | 12.93 | 15.05 | 38.40 | 50.60 | 23.48 |
| | (22.59) | (28.71) | (33.61) | (35.84) | (48.70) | (50.02) | (42.39) |

*Note: Preference* has the scale of 0–100. The *Weeks Willing to Wait* has the scale of 0–52. The subjects can also choose "never receiving this vaccine", in which case the willingness to wait of that observation is not counted.

We estimate the following model to examine the evolution of vaccine preferences,

$$\begin{aligned}(\text{Preference}_{i,v}^{Post} - \text{Preference}_{i,v}^{Pre}) = & \alpha + \sum_{l \in \mathcal{A}} \beta_l (\text{Effectiveness}_{i,v}^{l,Post} - \text{Effectiveness}_{i,v}^{l,Pre}) \\ & + \sum_{k \in \mathcal{D}} \delta_k \text{DemandCategory}_{i,v}^{k} + X_i' \xi, \end{aligned} \tag{1.6}$$

where the $\mathcal{D}$ includes the six demand categories ({Selected, Not Selected Top 3, Not Top 3} $\times$ information received or not),[19] and $\mathcal{A}$ is the set of characteristics: efficacy, hospital prevention rate, adverse event rates, and severe adverse event rates. In short, this model captures how the difference in preferences changes in the subjects' demands for vaccine information and the updates of their beliefs of vaccine effectiveness. If $\beta_l > 0$, the subjects' preferences are positively correlated with the belief change; that is, the subjects (rationally) react to the belief change. We can further identify the treatment effect within the groups Selected, Not Selected Top 3, and Not Top 3 by taking the difference between the coefficients $\delta_k$ of the received and not received within the same group.

The results are summarized in Table 1.6. Column (1) shows the result for stated preference. We find that when there is a positive change in beliefs about the vaccine effectiveness (higher efficacy/hospital prevention rates or lower adverse event rates), the subjects also hold a more positive view of the vaccine. Furthermore, we find that unconditionally, when a subject receives information about the Selected Top 3 vaccines, the subjects' preferences for that vaccine will increase by 2.77, which is a 0.15 standard deviation of the average preference change. However, we did not see as strong effects in weeks willing to wait, which is shown in column (2). While the signs are consistent with the results about the preference, the effect sizes are not significant enough to be

[19] *Not received not top 3* is set as the baseline group.

detected.

In terms of the *extensive margin*, we look at the responses of *never taking this vaccine* attached to the willingness-to-wait question. If a subject does not want to receive the vaccine even when there is no waiting time, the subject can check the option *never taking this vaccine*. The columns (3) and (4) in Table 1.6 show the results of this extensive margin, where the dependent variable is the binary variable that represents whether a subject checked the *never taking* option for the very vaccine post-treatment. Column (3) includes only the observations that the *never taking* option is selected pre-treatment; hence, we can interpret the result as the *extensive margin* of the vaccine reception. We find that receiving the vaccine information the subjects select makes the proportion of the never-takers drop by 18.38%, while the information only decreases the proportion of the never takers by 10.53% for the non-selected top 3 and by 2.87% for non-top 3. Column (4) includes only the observations that do not click the *never taking* option, and there is no notable difference in treatment effects found between different information demand groups. This result provides another piece of evidence that our subjects follow the rational information acquisition framework, as the information they select really persuades them to switch the decision (considering the vaccines that they may refuse to take before the treatment).[20]

**Result 3** (Decision with Information)**.** *If a subject receives the vaccine information she selected, the preference of that vaccine will increase, and she will be persuaded to take that vaccine if it was not considered before. Additionally, subjects' preferences of vaccines positively correlates with the upward belief changes in vaccine effectiveness.*

[20]We note here that among the observations of the selected information, only 5% are about the vaccines not considered before the intervention. The result we provide here should only be interpreted as suggestive evidence of pivotal information choice.

Table 1.6: Vaccine Preference and Beliefs in Effectiveness

| | PostPreference − PrePreference | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Preference (0-100) | WTW (0-52) | Never Take | After Treatment (%) |
| *Belief Differences* | | | | |
| Efficacy | 0.08** | 0.01 | 0.04 | -0.09* |
| | (0.03) | (0.02) | (0.09) | (0.04) |
| Hospitalization | 0.11*** | -0.01 | -0.18* | -0.04 |
| | (0.02) | (0.02) | (0.07) | (0.03) |
| Adverse Events | -0.05** | 0.00 | 0.10* | 0.02 |
| | (0.02) | (0.01) | (0.05) | (0.02) |
| Severe Adverse Events | -0.03 | -0.01 | -0.00 | 0.02 |
| | (0.02) | (0.02) | (0.07) | (0.02) |
| *Information Demand* | | | | |
| Selected Top 3 – Received | 1.41 | 1.50* | -24.65*** | -5.52*** |
| | (0.80) | (0.62) | (7.07) | (1.33) |
| – Not Received | -1.35 | 1.37 | -6.27 | -4.34** |
| | (1.22) | (0.81) | (7.64) | (1.62) |
| Not Selected Top 3 – Received | -1.64 | 2.59* | -16.90* | -2.00 |
| | (1.61) | (1.27) | (8.41) | (1.96) |
| – Not Received | 0.33 | 0.81 | -6.37 | -5.50** |
| | (1.29) | (1.11) | (9.46) | (1.77) |
| Not Top 3 – Received | -1.16 | -0.36 | -2.87 | -1.72 |
| | (1.34) | (0.92) | (3.41) | (2.05) |
| Constants | 1.63 | 1.20 | 78.98*** | 11.59*** |
| | (2.07) | (1.65) | (7.34) | (2.43) |
| Treatment Effects in ... | | | | |
| Selected Top 3 | 2.77** | 0.13 | -18.38 | -1.19 |
| | (1.02) | (0.76) | (9.90) | (1.12) |
| Not Selected Top 3 | -1.97 | 1.79 | -10.53 | 3.51 |
| | (1.91) | (1.56) | (12.44) | (2.19) |
| Not Top 3 | -1.16 | -0.36 | -2.87 | -1.72 |
| | (1.34) | (0.92) | (3.41) | (2.05) |
| Subgroup | All | All | Never Take | Willing to Take |
| Observations | 3160 | 3160 | 759 | 2401 |
| Subjects | 632 | 632 | 491 | 616 |
| $R^2$ | 0.052 | 0.025 | 0.11 | 0.035 |
| Mean of Dep. Variable | 0.035 | 0.56 | 86.0 | 4.00 |
| Subgroup | All | All | Never Take | Willing to Take |

*Notes.* Clustered (at subject level) standard errors in parentheses. The subjects' family income, college majors, and sex are controlled. The dependent variables of the first two columns are the differences between the preference variables before and after the treatments. The first column is the changes in preference evaluations of the vaccines, and the second column is the changes in numbers of weeks that the subjects are willing to wait for the vaccines. The dependent variable of the last three columns is the binary variable of whether the subject never takes the vaccine; the coefficients are measured in percentage term. Column (4) includes observations reported *never taking that vaccine* prior to the treatment, and column (5) includes observations reported *willing to wait for that vaccine* prior to the treatment. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

## 1.6 Conclusion and Discussions

We use an online experiment about COVID-19 vaccines to examine whether people's acquisition of information and belief updates cohere with the rational information acquisition framework. Overall, our empirical findings provide suggestive evidence that our subjects are following this standard theory framework. We find that the subjects prefer to select the information about the more effective vaccines. After the subjects receive their selected information, they will be persuaded more, and they will prefer that vaccine more and thus change their decisions. The patterns we find show that our subjects are consciously choosing the *pivotal* information, and they update their beliefs and decisions accordingly.

With our design dissecting the stages of information acquisition, we also document one incongruity from theory in information selection—we find people are more willing to select the information about the vaccines that they are more familiar with. Since such information reduces less uncertainty compared to information about less-familiar vaccines, this inverse selection leads to potential sub-optimality of information selection. This finding provides one potential policy implication that the government can encourage people to acquire information that they may not actively seek. Using the context of vaccines as an example, when there is a new vaccine with similar effectiveness, the government can incentivize people to read the information about the vaccine. This makes people more familiar with the vaccine, and thus people may be more willing to seek information about that vaccine afterward, which mitigates the sub-optimality of the information selection.

There can be some potential improvements in our experiment. First, the elicitations of beliefs and vaccine preferences are not incentivized. As we attempted to keep the environment of the experiment as natural as possible for the subjects, we lost the capability of using incentive-compatible elicitation designs commonly applied in the lab.

Consequently, we need to assume that our subjects report their beliefs and preferences unbiasedly, and we admit that our dataset may be more noisy. Second, while the variance of the beliefs is one important factor in the rational information acquisition framework, we were not able to carefully elicit the variances of the beliefs. To best proxy the variance or the "uncertainty" of the beliefs, we ask the subjects about their familiarity with the vaccines. Although this may partially capture the dispersion of the beliefs, it may be correlated with their cognitive uncertainty (see discussions in Enke and Graeber (2023).)

Our results can also extend to other environments sharing similar features as ours—environments with correlated states and information acquisition, for instance, stock markets, real estate, etc. As our design structure is compatible with control correlated signal structures, we believe our design can help future studies better identify the mechanism of information selection and belief updates under various real-world contexts.

# Chapter 2

# The First Vote in Referendum and Update from Information

*with Ming-Jen Lin*

## 2.1 Introduction

Political polarization has seized attention in recent years. Several political science and psychology studies have documented the positive correlation between vote-casting and polarization (see Beasley and Joslyn (2001), Bølstad et al. (2013)). One possible channel causing this correlation is cognitive dissonance: people do not vote against their past decisions to avoid inconsistency in their choices. This claim is, however, hard to test empirically due to a clear endogeneity in the voting action, as only voters with strong enough intention to vote will select to turn out.

Some recent studies address this self-selection issue by implementing the quasi-random treatments: eligibility. Ineligible citizens can never vote regardless of their intention to vote; therefore, by comparing the behavior between the eligible and ineligible voters, we can identify the effect of the voting intention on people's decisions. For example, Mullainathan and Washington (2009) finds the eligible voters are two times as polarized after their first votes in the presidential elections, and Dinas (2014) finds the eligible voters have stronger party identification. These studies use different sets of survey data (the National Election Study (1976–1996) and the Youth-Parent Socialization Panel Study (1965–1997) in the US) and suggest a similar behavioral pattern. Nonetheless, how cognitive dissonance occurs during people's decision-making process remains unclear. Does cognitive dissonance stop voters from updating their beliefs from information and thus become polarized? Or does cognitive dissonance selectively affect people's updating from information?

In this study, we implement the eligibility instrument to test how the information channel contributes to voting stickiness. We exploit the 2021 Taiwanese Referendum as the environment and examine how information persuades people. We recruited subjects who were either 17 or 18 years old on the referendum day where the subjects aged 18 were eligible to vote in the referendum, and the others were not. We first surveyed our subjects' voting decisions and supportiveness of the propositions in the referendum within the two weeks after the referendum.[1] Three months later, we called the subjects back and sent them the treatment news articles about the propositions voted, where the articles were either *positive*, *negative*, or *neutral* to the propositions. After the subjects read the articles, we asked them about their hypothetical choices if a referendum with the same propositions were held again. Since the treatments were randomly assigned, we can evaluate how different information would influence people's votes and perceptions of the propositions. By examining the difference in treatment effects between the eligible and ineligible subjects, we can detect the influence of the "first vote" through information.

[1] For ineligible voters or voters who did not turn out to vote, we surveyed their hypothetical decisions. We will discuss the design details in Section 2.4.

We find that eligible subjects are more triggered by the *positive* treatment on protecting algal reefs and the *negative* treatment on reopening a nuclear power plant. The eligible subjects' overall supportiveness moves more than the ineligible subjects toward the corresponding sides that the treatment articles indicate. When we look into the vote changes, we find the positive treatment of algal reefs makes eligible voters who supported the proposition in the referendum ("yea voters") stick to their votes more. The negative treatment of nuclear power plants makes the eligible "nay voters" more sticky. These results suggest that information may partially contribute to the formation of political polarization.

We further look into the mechanisms that could lead to the heterogeneity in treatment effect from partisan information between the eligible and ineligible subjects. Among those who care about environmental issues the most, there is a more profound difference between the eligible and ineligible subjects. This finding suggests that the effect of the first vote can interact with the voters' ideology. The information can trigger stronger vote stickiness as the first vote can be an active assertion to these environmental voters. We also examine whether the pre-treatment awareness of or knowledge about the propositions leads to the heterogeneity we discover, but we do not find any evidence supporting this channel. We thus conclude that the interaction between information and the action of voting emerges in a more issue-oriented manner.

The identification of our study benefits from several advantages of the empirical context. First, the eligible age for a referendum in Taiwan is lower than the eligible age for elections, so our subjects have yet to vote in any elections. The diverged eligibility bar deteriorates the potential channel from partisan preferences due to voting histories. Second, none of the propositions was adopted in the referendum as the turnout rates did not exceed the threshold. As it remained *status quo*, no policy change could affect the subjects' information acquisition after the referendum. Third, the assent and the dissent votes were roughly equal. Therefore, effects arising from the unbalanced voting results (*e.g.*, the bandwagon effect) can only play a minimal role in our study.

Our study contributes to the literature on information and political behavior. In recent work, Baysan (2022) utilizes the 2017 referendum in Turkey and finds that providing information can cause more severe polarization. Enríquez et al. (2024) introduce the information about government expenditure irregularities on social media during the 2018 Mexican municipal elections. They find that information directly influences the election outcome and initiates the discussion among the community members.

This study also contributes to the research on young voters' political participation. Several works in political science study voters' early political participation experience. Breeze et al. (2017) and Breeze et al. (2021) study young voters' political participation after the 2014 Scottish independent referendum, and they find in the interviews that participation in the referendum makes voters more willing to be involved in politics. Our study qualitatively assesses how early electoral experience can influence people's future political participation. To our knowledge, we are the first study that experimentally observed how information affects young voters' political beliefs and how voting acts in young voters' political belief formation.

The chapter proceeds as follows. In Section 2.2, we introduce the political background of the 2021 Taiwanese Referendum. We then describe our identification strategy in Section 2.3 and our experimental design in Section 2.4. To claim the balancedness between our eligible and ineligible subjects, we present statistics about the characteristics before the treatments in Section 2.5. We present our results in Section 2.6. Section 2.7 concludes the chapter.

## 2.2 The Political Background of the 2021 Taiwanese Referendum

### 2.2.1 Referendums in Taiwan

The Referendum Act in Taiwan was enacted in December 2003, which allows Taiwanese citizens to propose, amend, or abolish the laws. The first referendum in Taiwan was held in 2004. Since the first referendum, there were in total 21 national propositions (including one constitutional propositions) voted in four referendums. The voters have to hold Taiwanese citizenship to be eligible to vote in a referendum.[2] The eligible age in a referendum is 18, while the eligible age in elections is 20.[3]

To propose a proposition, the proposer should submit a petition to the Central Election Commission (CEC) for qualification check. After qualified, the petition should gather at least 1.5% of the voters' signature to be officially proposed as a proposition.[4] The proposal will then be voted on the next designated date of referendum.

The referendum vote is anonymous, without any pre-registration. All eligible voters are automatically enrolled. To vote in a referendum, the voter should go to the assigned polling station near the voter's registered residence in person; no remote voting system such as mailing vote is available.

Referendums in Taiwan follow majority rule with a quota. For a proposition to be approved, two conditions have to be satisfied: if (1) valid ballots of assent are more than ballots of dissent and (2) reach 1/4 of eligible voters (Article 29, Referendum Act).[5] After

[2]Additionally, the eligible voters have to maintain residency in Taiwan for the six months before the referendum and must be without the commencement of guardianship.

[3]The eligible age in a referendum was lowered to 18 after the 2017 amendment of the Referendum Act. Before the amendment, the eligible age in a referendum was 20, which was the same as the eligible age in elections.

[4]The number of voters is estimated by the number of total eligible voters in the last presidential election. In the 2021 referendum, the number of the signatures required is approximately 290,000.

[5]The second condition was implemented after the 2017 amendment of the Referendum Act. Before

a proposition is approved, the Executive Yuan (the executive branch of the Taiwanese government) and the Legislative Yuan (the national legislature of Taiwan) should either terminate the related laws or regulations contradicting the approved proposition or initiate the related laws within a certain period.[6] If a proposal is vetoed, another proposal regarding the same matter will not be allowed to be raised within two years after the referendum.

### 2.2.2 The 2021 Referendum: Background and the Propositions

According to the 2019 amendment of the Referendum Act, the referendum can only be held on the fourth Saturday of August every two years. Hence, the 2021 referendum was original set to be held on 28th August 2021. However, due to the COVID-19 pandemic, it was postponed to 18th December 2021.[7] There were approximately 20,000,000 eligible voters in this referendum, where approximately 400,000 (2%) of them were aged 18-19.

Four propositions were voted in the 2021 referendum, which are listed below, together with the actual questions on the ballot.

- [Energy, Environment] Reactivating nuclear power plant construction

  *"Do you agree the activation of Taiwan's mothballed Fourth Nuclear Power Plant?"*

- [Health, Economy, Politics] Banning ractopamine-contained pork imports

the 2017 amendment, the turnout rate was acquired to be exceeding 50% for a proposition to pass. To boycott the propositions, the campaigns from the opposing parties often asked their supporters to abstain from voting in the referendums. As a result, none of the propositions prior to the 2017 amendment passed the turnout rate threshold, and thus none of them was approved.

[6]See Article 30 of the Referendum Act for detailed information. We provide an example of how the referendum results are implemented. The propositions "*Restricting marriage under Civil Code to one man and one woman*" and "*Protecting rights of same-sex marriage couples outside of the Civil Code* were both passed in 2018 referendum. Consequently, in 2019, same-sex "marriage" was legalized under *Act for Implementation of Judicial Yuan Interpretation No. 748*, which is not part of the Civil Code, while it is very similar to the hetero-sex marriage defined in the Civil Code.

[7]The postpone was announced on 2th July 2021. The eligible voters were still those who were over 18 years old on 28th August 2021. That is, only who were born before 18th August 2013 were eligible. The postpone did not change the eligibility age bar.

*"Do you agree that government should put a ban of the importation of pork, internal organs and pork products containing ractopamine (β-adrenergic receptor agonists)?"*

- [Politics] Holding referendums alongside elections
  *"Do you agree within six months from the date the referendum be announced establishment, if there is a national election take place during the period, and in accordance with the provisions of the Referendum Act, that the referendum shall be held in conjunction with the national election?"*

- [Energy, Environment] Keeping natural gas terminal out of algal reefs
  *"Do you agree to relocate the construction site of CPC Third LNG Receiving Terminal away from the coastal and sea areas of Taoyuan's Datan Algae Reef? (The coastal area from the estuary of Guanyin River in the north to the estuary of Xinwu River in the south, and the sea area stretching out five kilometers parallelly alongside the lowest tide line of the aforementioned coast.)"*

We introduce the political background of the four propositions below.

**Reactivating nuclear power plant construction**

The nuclear power plant of the matter is the fourth nuclear power plant in Taiwan, located in Lungmen, New Taipei City. The construction started from 1999. In 2000, Shui-bian Chen from the Democratic Progressive Party (DPP) was elected as the new president. Due to the increasing safety concern after the 1999 earthquake in Taiwan and the DPP's anti-nuclear ideology, the construction of the fourth nuclear power plant was suspended. The suspension caused the conflict between the DPP and the pan-Blue coalition,[8] which was the majority in the Legislative Yuan and generally supported nu-

[8]The pan-Blue coalition refers to a collection of parties with ideology close the former incumbent party, the Kuomintang (KMT), where blue is the representing color of the KMT. The pan-Blue coalition usually includes: the KMT, New Party (CNP), People First Party (PFP), and other smaller parties.

clear power. In 2001, the government and the congress agreed to restart the construction of the power plant. Nonetheless, 220 billion NTD (approximately 6.5 billion USD) of additional costs was generated due to the suspension, and the expected completion date was largely delayed.

After the Fukushima nuclear disaster in 2011, the safety issue of the nuclear power plants attracted people's attention again. The DPP (which became the opposition party after the 2008 election) and other organizations ran for campaigns against nuclear power. In 2014, the Prime Minister Chiang announced the freeze of the construction again, sealing the completed and fuel-loaded first reactor.

Starting from 2018, the Taipower company removed and shipped the unused nuclear fuel rods back to the US. As the incumbent party, the DPP, planned to shut down all nuclear power plants by 2025, the construction of the fourth nuclear power plant was also planned to be halted permanently. However, since the proposition "*repealing the article in the Electricity Act about stopping all nuclear power plants by 2025*" was adopted in the 2018 referendum, promoters of nuclear power initiated the petition of reactivating the fourth nuclear power plant. The petition was approved and then became a formal proposition in the 2021 referendum.

The KMT and pan-Blue parties campaigned in favor of this proposition, while the DPP and New Power Party (NPP) campaigned against this proposition. The Taiwan People's Party (TPP) did not state their position in this question.

**Banning Ractopamine-contained Pork Imports**

Ractopamine is a type of $\beta$-adrenergic agonists, which is used as an animal feed additive to increase the meat production. The Food and Drug Administration in the US (FDA) approved the use of ractopamine in swine in 1999, with the maximum residue limits of 50 parts per billion (ppb). However, the usage of ractopamine is banned in the

EU and several countries, including Taiwan. In 2012, the Codex Alimentarius Commission (Codex) set the limit to be 10 ppb for the muscle cuts of pork and beef, which is 1/5 of the FDA regulation.

The imports of beef and pork from the US have been debated between the two major parties in Taiwan, the DPP and the KMT. The imports of ractopamine-contained beef and pork were banned in 2006 by the President Chen from the DPP. However, as the trade bargaining between Taiwan and the US proceeded from 2008, the incumbent parties (either the KMT or DPP) tended to remove the restrictions in exchange for better trade conditions with the US. In 2012, the restriction of ractopamine-contained beef was removed by President Ma from the KMT. After 14 years of banning the imports of ractopamine-contained pork, President Ing-wen Tsai removed the restrictions in 2020, admitting the Codex maximum residue limits of 10 ppb.

In 2020, the KMT Legislator, Wei-chou Lin, led and proposed the petition of banning the ractopamine-contained pork imports again, which was approved as a proposition in 2021 and would be voted in the referendum. The KMT, NPP, PFP, and TPP campaigned in favor of the proposition, while the DPP campaigned against the proposition.

#### Holding referendums alongside elections

Lowering the restriction of proposing a proposition in referendums in the amendment of the Referendum Act in 2017, the 2018 referendum consisted of ten propositions, alongside with the 2018 local elections. This large referendum together with the election caused logistic problems; some voters could not even enter the polling station by the termination time, and the vote counting did not finish until the midnight. In addition, the overwhelming amount of information about the referendum and elections caused concerns of the voters' underconsideration. To fix the issues, the DPP led the amendment of the Referendum Act in 2019, in which the referendum is designated a separate voting day than elections. In the latest amendment of the Referendum Act, the referendums should be held on the fourth August every two years.[9]

However, the KMT claimed that the isolated voting day would lower the turnout rate and would prevent any proposition from passing. Furthermore, the additional voting other than the elections would increase the unnecessary government expenditure. Consequently, the KMT Chairperson, Johnny Chiang Chi-chen, led the petition of re-binding the referendum and the elections. Specifically, the proposition proposed that if a proposition is approved within the six-month window before a national-wide election, the referendum should be held on the same day of the election. The proposition was approved in 2021 and then voted in the referendum.

The DPP was the only major party campaigned against the proposition. In addition to the potential logistic issues, the DPP also claimed that the referendum could be used as part of the propaganda in the elections, so that the referendum would lose its neutrality. The KMT and NPP campaigned in favor of the proposition. The TPP did not state their position in this proposition.

#### Keeping natural gas terminal out of algal reefs

The liquid natural gas (LNG) terminal of the matter is planned to locate at Guantang in Taoyuan City, which is right in the Datan Algal Reef. The LNG terminal is part of the DPP's plan of phasing out the fossil fuel and energy transfer. The LNG imported from this terminal will be used in the nearby gas-fired power plant as an alternative of nuclear power.

However, some environmental organizations criticized the policy because the construction of the LNG terminal can heavily damage the algal reef and the ecosystem around it. In 2020, the "Cherishing algal reef" group and its leader, Chung-cheng Pan,

[9]Currently it is held in every odd years, which avoids the general and local elections in even years.

ran movements for submitting the referendum petition. The KMT endorsed the petition in 2021 and promoted replacing gas-fired power with nuclear power. The petition was submitted and approved later, and would be voted in the referendum.

In response to the concerns from the environmental organizations, the DPP government amended the design of the terminal to reduce the impact to the algal reef. Nonetheless, the occupied area of the LNG terminal was still 23 hectares (approximately 57 acres), while the organizations insisted that the LNG terminal should never be initiated to avoid any impact on the algal reef ecosystem.

The DPP was the only major party campaigned against the proposition. The KMT, TPP, and NPP campaigned in favor of the proposition.

The party endorsements are summarized in Table 2.1.

### 2.2.3 The Results of the Referendum

The results of the referendum were announced on the same day of the referendum. None of the propositions were adopted as the assent votes were less than the dissent votes in each of the propositions. The turnout rates and the vote proportions are summarized in Table 2.1.[10]

## 2.3 Identification Strategy

This paper answers the following question: "does casting the first vote influence how people are persuaded by further information?" Nonetheless, there is a clear source of endogeneity if we directly compare the persuasion between the voted and never-voted subjects. For example, the subjects who turned out to vote might have stronger prior

[10]As a reference, the turnout rate in 2018 referendum (held alongside the local elections) was approximately 55%.

Table 2.1: The Party Campaign and Results of the Referendum

| | Party Campaign | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|
| Propositions | DPP | KMT | TPP | NPP | Turnout | Assent | Dissent | Adopted? |
| Nuclear Power Plant | − | + | ◯ | − | 41% | 47% | 53% | No |
| Banning Pork Imports | − | + | + | + | 41% | 49% | 51% | No |
| Combining Referendum | − | + | ◯ | + | 41% | 49% | 51% | No |
| Protect Algal Reef | − | + | + | + | 41% | 48% | 52% | No |

*Notes.* *Note.* The four parties with the most seats in the Legislative Yuan are listed, by the order of the percentage of representatives. "+" in party campaigns means the party campaigned in favor of the proposition. "−" means the party campaigned against the proposition. "◯" means the party did not state the position about the proposition. The turnout rate is the proportion of the turned out voters among all eligible voters. The assent and dissent rates are the proportion of assent or dissent votes among all valid votes. All four propositions were not adopted as the assent rates were lower than dissent rates.

beliefs, so they may react to the information differently to the non-voted subjects. If this is the case, we cannot distinguish the effects from casting votes and the effects from their stronger prior beliefs.

To exclude the self-selection of the voter's turnout, we recruited the subjects just around the eligible age of voting in a referendum in Taiwan. Namely, we recruited the subjects who were 17 to 18 years old, while the subjects who were below 18 on the referendum day were ineligible to vote in the referendum. As the ineligible voters are *never* able to vote regardless of their strength in beliefs, when can compare the persuasion on the eligible and ineligible voters, the difference will be coming from the voters who intend to vote, while one group is allowed to vote and the other group is prohibited to vote. If it is almost random for the voters to be eligible, and if the eligible voters are qualitatively similar to the ineligible voters, we can claim the difference on these intended voters in eligibility captures the difference in whether the voters cast their first votes.

We describe our specification formally. Let $Vote^0$ be the voting decision before receiving treatments and $Vote^1_t$ be the decision if the voter receives treatment $t$. We denote the change in voting decisions before and after treatment $t$ as $VoteChange_t = Vote^1_t - Vote^0$.

Let $VoteChange_c$ be the vote change after receiving the control treatment (non-partisan news articles under our context). Then we further denote

$$\Delta\, VoteChange_t = VoteChange_t - VoteChange_c$$

to be the potential difference in the vote changes between the cases that the voter receives the treatment $t$ and the control treatment. That is, this is the estimand of the treatment effect after receiving treatment $t$.

We make the following assumptions.

**Assumption 5.** Let *Voted* be the status that whether a voter have voted before. Let $\Delta\, VoteChange_t(Voted)$ be the potential difference for voted voters in vote changes between treatment $t$ and the control treatment, and $\Delta\, VoteChange_t(NotVoted)$ be the potential difference for not voted voters. Furthermore, let *Eligibility* be the state that whether a voter is eligible to vote, and *Voting* be whether the voter is intended to vote. Then

(1) $(\Delta\, VoteChange_t(Voted), \Delta\, VoteChange_t(NotVoted)) \perp Voted$

(2) $(\Delta\, VoteChange_t(Voted), \Delta\, VoteChange_t(NotVoted)) \perp Eligibility \mid Voting$

(3) $Eligibility \perp Voting$

The central idea of the assumptions are (1) voting history does not affect the potential outcome, (2) given the voting intention, the eligibility does not change the treatment effects on voting changes, and (3) the eligibility does not change whether the voting intention. In other words, the eligible and ineligible voters are similar to each others.

Given Assumption 5, we can derive

$$
\begin{aligned}
&\mathbb{E}\left[\Delta\, VoteChange_t | Eligible\right] - \mathbb{E}\left[\Delta\, VoteChange_t | Ineligible\right] \\
=&\mathbb{E}\left[\Delta\, VoteChange_t | Eligible,\, Voting\right] \Pr\left(Voting | Eligible\right) \\
&+ \mathbb{E}\left[\Delta\, VoteChange_t | Eligible,\, NotVoting\right] \Pr\left(NotVoting | Eligible\right) \\
&- \mathbb{E}\left[\Delta\, VoteChange_t | Ineligible,\, Voting\right] \Pr\left(Voting | Ineligible\right) \\
&- \mathbb{E}\left[\Delta\, VoteChange_t | Ineligible,\, NotVoting\right] \Pr\left(NotVoting | Ineligible\right) \\
=&\mathbb{E}\left[\Delta\, VoteChange_t | Voted\right] \Pr\left(Voting\right) \\
&+ \mathbb{E}\left[\Delta\, VoteChange_t | NotVoted\right] \Pr\left(NotVoting\right) \\
&- \mathbb{E}\left[\Delta\, VoteChange_t | NotVoted\right] \Pr\left(Voting\right) \\
&- \mathbb{E}\left[\Delta\, VoteChange_t | NotVoted\right] \Pr\left(NotVoting\right) \\
=&\left(\mathbb{E}\left[\Delta\, VoteChange_t | Voted\right] - \mathbb{E}\left[\Delta\, VoteChange_t | NotVoted\right]\right) \Pr\left(Voting\right) \\
=&\mathbb{E}\left[\Delta\, VoteChange_t(Voted) - \Delta\, VoteChange_t(NotVoted)\right] \Pr\left(Voting\right),
\end{aligned}
$$

where the difference in the expectation in the last line is the estimand desired. Note that only eligible voters who intend to vote can vote, so we can replace the eligibility and voting intention combinations with the voting history ($Voted$).

## 2.4 Experiment Design

### 2.4.1 The Experimental Phases

Figure 2.1 depicts the experiment timeline. The first phase of the experiment started after the 2021 Referendum, which was held on Dec. 18th, 2021. The second phase was conducted from Mar. 18th to the beginning of May in 2022. We describe the logistics and the surveys in the rest of this subsection.

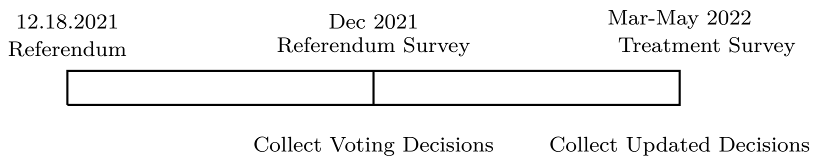



Figure 2.1: Experiment Timeline

#### Referendum Survey

In the first phase, *Referendum Survey*, we posted the survey links on Facebook and Instagram via Facebook Ads.[11] We targeted the Taiwanese Facebook/Instagram users who were aged 17-19. When the subjects entered the survey, we asked their nationality and birthday to further screen the subjects.[12] After the qualified subjects completed the survey, the incentive of a gift card of 50 NTD (approximately 1.5 USD) was provided. As an additional incentive, each subject had 1% chance to win a 500 NTD gift card (approximately 15 USD).

The survey takes about 15 minutes to complete. In the survey, we asked the subjects' decisions in the referendum, including whether they turned out to vote and their votes in each proposition. If the subjects were not eligible or did not turn out, we asked their hypothetical decision if they had turned out.[13] If the subjects reported "casting invalid votes" or "abstaining from voting", we asked their decisions if they were required to vote

[11] Facebook Ads allows us to post a package of *ads* includes the link of the survey with a thumbnail. Figure 2.2 demonstrates the looking of the ads. The potential subjects could click the ads and start the experiment. Based on the preset budget, Facebook Ads automatically sent the ads to their users. Facebook Ads also screens the users satisfy the conditions set by the us (*e.g.*, age, location.) Facebook Ads screens the subjects with the user information in their database. The readers should be reminded that some information provided by the users may not be true.

[12] The subjects were required to provide school email addresses with "`.edu`" for validation. We use this to screen subjects who could have been without the age range.

[13] The question reads: "*If you were eligible and turned out in the referendum on 18th Dec., how would you have voted?*"


Figure 2.2: The Demo of Ads on Facebook and Instagram

between "yea" or "nay". For each of the propositions, we further asked their interests about the issue, including their subjective interests and information acquisition behavior.

Finally, we asked their political preferences and participation, including their support on the parties, evaluation of importance in various issues, and their participation in political events. We also include questions about daily media consumption.

After ruling out the subjects who were born before 2002 or after 2004 (not 17-19 years old), the valid sample size is 828, where 405 subjects are eligible.

### Treatment Survey

In the second phase, *Treatment Survey*, we sent out the treatment articles followed by comprehension quizzes and a survey to the qualified subjects who completed the referendum survey. After the subjects completed the whole survey, they would receive a fixed payment of a gift card worth 150 NTD (approximately 5 USD). Additionally, they could win a bonus of a gift card worth 500 NTD (approximately 17 USD) incentivizing them to carefully read the treatment articles and then correctly answer the comprehension quizzes. Among 9 quiz questions, if a subjects correctly answered $n$ questions, the probability that she would win the bonus is $n\%$.

Each subject will receive one treatment article about the each proposition. Specifically, all subject would read the articles about *pork import*, and *combining referendum*, and each of the subjects was randomly assigned to read one article either about *nuclear power plant* or about *algal reef*.[14] Hence each subject would read three treatment articles. For each proposition, the subjects could receive the article supported the proposition, opposed the proposition, or neutrally describe the background of the proposition. The positions of the articles were randomly assigned at proposition level; that is, a subject could receive a supporting article for one proposition while receive an opposing one for another proposition.

Each article would be followed by three reading comprehension questions; the questions were about the details in the articles that the subjects would not be able to answer correctly without carefully reading the articles. The subjects were then asked to evaluate the information they just read. They had to judge the position that the article held, reveal how informative the article was to them, and judge how much of the information was correct.

After reading the treatment article of each proposition, the subjects were asked the hypothetical questions about voting choices similar to the ones in *Referendum Survey*.[15] The subjects were also asked the question about their support of the proposition. If the subject did not receive any treatment article about the proposition, the subject would still receive questions about the voting decisions and the support of the proposition. The order of the propositions is randomly determined.

[14] We randomize the reception of the information between *nuclear power plant* and *algal reef* because the two topics are closely related. Stratifying the topics can prevent the interaction of the treatment effects between different topics.

[15] Specifically, the questions reads: "*If the proposition were voted again tomorrow, how would you vote?*"

The detailed list of questions are included in the online appendix.

### 2.4.2 Treatments

The treatment articles were taken from the news articles. For the propositions in the referendum, we collect the treatment articles from *PTS News Network (PNN)*, which is a news agency executed by Taiwanese *Public Television Service (PTS)*. PNN summarized the supporting and the opposing opinions for each of the propositions, organized with different aspects of the propositions. We split the summary into the supporting and opposing parts. For the neutral articles, we summarized the background information about the propositions. The summary included only facts about the proposition, avoiding the timely arguments. In the survey, we asked the subject to evaluate the position of the treatment articles; the perception from subjects was consistent with the intended position.

The length of the treatment articles for the same proposition were balanced among the supportive, opposing, and neutral article. To reduce the influence from the subjects' partisan ideologies, the names of political parties and politicians were removed from the treatment articles.

## 2.5 Baseline Summary Before the Treatments

The key hypothesis this paper implements is that the eligible subjects and the ineligible subjects are similar, and the effect from the voting experiences is homogeneous for the eligible and ineligible subjects. This hypothesis is, however, not directly testable. In this section, we compare some key attributes regarding this experiment. We claim that the two groups of the subjects have arguably similar characteristics, so there is no strong evidence supporting that the two groups would have different outcomes.

### 2.5.1 Attrition and Sample Selection

Our experiment has two waves of the surveys; the first one collects the subjects' voting decisions in the referendum, and the second one gives out the treatment articles. Table 2.2 summarizes some key statistics between the two waves. In the column *Sample Recruited*, we list the statistics for all subjects attended the first wave survey (after referendum); in the column *Sample Treated*, we we list the statistics for all subjects who came back for the second wave survey (treatments). In general, the subject pool stayed in second survey is not qualitatively different to the recruited subject pool.

As our identification strategy exploits the subjects' eligibility, we limit our estimation sample to the subjects who were born one year before and after the eligibility cutoff (subjects who were born between 8/28/1992 and 8/28/1994). To further strengthen the validity of the sample, we exclude the subjects who correctly answered less than 33% of the reading comprehension questions after each treatment articles. Specifically, in our final sample, we exclude subjects correctly answered no more than 3 out of 9 questions. The summary is shown in the last two columns of Table 2.2. Roughly 70% of treated subjects (404 out of 573) remain in our estimation sample. There is no evidence of unbalanced removal of either eligible or ineligible subjects.

### 2.5.2 Knowledge about the Referendum and Political Participation

One common argument against the identification strategy is on the prior knowledge of the voters. Since the Referendum Act has been amended for years, the eligible voters should be aware of the fact that they would vote in this referendum, thus they collect more information about the referendum and may behave differently when they see information. In this subsection, we show evidence that the eligible and ineligible voters are similarly

Table 2.2: Summary Statistics From the Referendum Survey

| | *Sample Recruited* | | | *Sample Treated* | | | *Estimation Sample* | | |
|---|---|---|---|---|---|---|---|---|---|
| | Eligible | | Ineligible | Eligible | | Ineligible | Eligible | | Ineligible |
| Turn Out Rate | 49% | *** | 80% | 49% | *** | 82% | 51% | *** | 84% |
| *"Yes" Votes on Propositions* | | | | | | | | | |
| Nuclear | 49% | * | 42% | 49% | * | 40% | 48% | * | 37% |
| Algal Reef | 51% | | 51% | 50% | | 50% | 53% | | 50% |
| Pork Import | 46% | | 44% | 47% | | 42% | 45% | | 40% |
| Combine Elections | 40% | | 39% | 41% | | 34% | 39% | | 36% |
| *Support of Propositions (0-10)* | | | | | | | | | |
| Nuclear | 5.4 | ** | 4.8 | 5.5 | ** | 4.7 | 5.3 | * | 4.6 |
| Algal Reef | 5.8 | | 5.6 | 5.8 | | 5.5 | 5.8 | | 5.5 |
| Pork Import | 5.6 | | 5.2 | 5.6 | * | 5.1 | 5.5 | | 4.9 |
| Combine Elections | 5.1 | | 4.9 | 5.1 | * | 4.6 | 4.9 | | 4.6 |
| $N$(Proportion) | 405(49%) | | 423(51%) | 280(49%) | | 293(51%) | 206(51%) | | 198(49%) |

*Notes.* (i) *Sample Recruited* include all observations who were recruited and took the *referendum survey*. *Sample Treated* include all observations who came back for the *treatment survey*. *Estimation Sample* include only the observations who were born between 8/28/1992 and 8/28/1994 and correctly answered more than 33% of the reading comprehension questions. (ii) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ in a pairwise test between eligible and ineligible voters.

knowledgeable about this referendum.

For each of the propositions, we asked the subjects to evaluated how much they were aware of the propositions. Figure E1 shows the distribution of the responses. We also surveyed how much they have researched about each proposition, where we show the distribution in Figure E2. We further encoded the different levels of the awareness and informedness with numeric levels. Table 2.3 shows the summary statistics of the responses.

We do not find clear sign of heterogeneity in awareness or the degree of research between eligible and ineligible subjects. The Kolmogorov-Smrinov tests do not detect any evidence of significant differences in the distributions. We still find a significant but mild difference in the mean awareness in the nuclear proposition between eligible and ineligible subjects. The ineligible subjects are more aware of the nuclear power plant than the eligible ones. However, if we split the subjects by whether they are at least somewhat aware, we do not see clear difference between eligible and ineligible subjects.

It can also be possible that the eligible voters care more about the referendum and politics. We give three measurements against this claim. First, we tested the subjects' general knowledge about this referendum by asking them to select the propositions voted in this referendum. We provided eight options of potential propositions (four of them were actually voted and the others were not), and we count the number of the correctly classified propositions (whether voted in this referendum). On average, 7.42 out of 8 propositions were correctly classified, and 73.76% of the subjects correctly classified all of the propositions. Second, we asked the subjects to evaluate how much they care about politics in general. 54.95% of the subjects responded at least "somewhat care". We list the average of the two measurements by eligibility in Table 2.3. We find no significant difference between the eligible and ineligible subjects.

Lastly, we surveyed whether our subjects have watched these public hearing sessions. For each of the propositions, there was a session of public hearing broadcast. Figure E3 shows the distribution of the responses from the eligible and ineligible subjects. For each of the propositions, there were only roughly 10% of the subjects fully watch the public hearing sessions, and around 45% of the subjects never watched these sessions. We still see no difference in the exposure to the public hearing between the eligible and ineligible subjects.

## 2.6 Experimental Results

### 2.6.1 Summary: The voting and preference changes

We first summarize the subjects' voting decisions in the post treatment survey. Table 2.4 summarizes the decisions reported in the post-treatment survey. We do not observe

Table 2.3: Knowledge about the Referendum

| Knowledge about Referendum | Eligible | Rank-sum | K-S | Ineligible |
|---|---|---|---|---|
| *Mean Awareness of the Propositions (1-7)* | | | | |
| Nuclear | 5.08 | * | | 5.35 |
| Algal Reef | 4.68 | | | 4.64 |
| Pork Import | 5.17 | | | 5.18 |
| Combine Elections | 4.50 | | | 4.48 |
| *Mean Informedness of the Propositions (1-5)* | | | | |
| Nuclear | 2.89 | | | 2.92 |
| Algal Reef | 2.62 | | | 2.65 |
| Pork Import | 3.00 | | | 2.95 |
| Combine Elections | 2.42 | | | 2.35 |
| Referendum Knowledge (0-8) | 7.46 | | | 7.38 |
| Politics Interests (1-7) | 4.43 | | | 4.54 |

*Notes.* (i) For the mean awareness, we encode the different levels of the descriptive awareness with numbers 1-7, where 1 represents "very unaware" and 7 represents "very aware". See Figure E1 for the detailed descriptions for levels. For the mean informedness, we encode the different levels of the research the subjects have done with numbers 1-5, where 1 represents "not researched at all" and 5 represents "researched thoroughly". See Figure E2 for the detailed descriptions for levels. The "referendum knowledge" comes from the question: "which of the propositions were voted in the last referendum", where we include in total 8 possible propositions. The score represents the number of propositions the subjects correctly classified. (ii) The "Rank-sum" column shows the significance level of Wilcoxon rank-sum test between eligible and ineligible voters, and the "K-S" column shows the significance level of Kolmogorov-Smirnov test. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

any clear inclination in the support of each of the propositions before or after the treatment. After the treatment, there is no significant difference in the vote shares or support between eligible and ineligible subjects. The decisions after the treatments are statistically similar to the pre-treatments except the ineligible subjects' yea votes in *nuclear* and the yea votes in *combine elections*.

Table 2.4: Summary Statistics From the Referendum Survey

| | *Pre-treatment* | | | *Post-treatment* | | *Pre-post Diff.* | |
|---|---|---|---|---|---|---|---|
| | Eligible | | Ineligible | Eligible | Ineligible | Eligible | Ineligible |
| *"Yes" Votes on Propositions* | | | | | | | |
| Nuclear | 48% | * | 37% | 51% | 49% | | ** |
| Algal Reef | 53% | | 50% | 53% | 47% | | |
| Pork Import | 45% | | 40% | 47% | 46% | | |
| Combine Elections | 39% | | 36% | 50% | 46% | *** | ** |
| *Support of Propositions (0-10)* | | | | | | | |
| Nuclear | 5.3 | * | 4.6 | 5.5 | 5.0 | | ** |
| Algal Reef | 5.8 | | 5.5 | 5.8 | 5.4 | | |
| Pork Import | 5.5 | | 4.9 | 5.4 | 5.2 | | |
| Combine Elections | 4.9 | | 4.6 | 5.4 | 5.1 | *** | *** |

*Notes.* (i) This table includes the subjects who were born between 8/28/1992 and 8/28/1994 and correctly answered more than 33% of the reading comprehension questions. (ii) $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ in a pairwise ranksum test between eligible and ineligible voters.

Figure 2.3 summarizes the vote shares before and after the treatments by propositions and treatments. We report an imbalancedness in pre-treatment vote shares between eligible and ineligible subjects in the negative treatment group for the proposition *Nuclear Power Plant* due to randomness. We do not observe other specific patterns in the pre-treatment vote shares. After reading the treatment articles, the votes change according to the treatment inclination. On average, positive news makes subjects more likely to vote for the propositions, and negative news makes them more likely to vote against them.

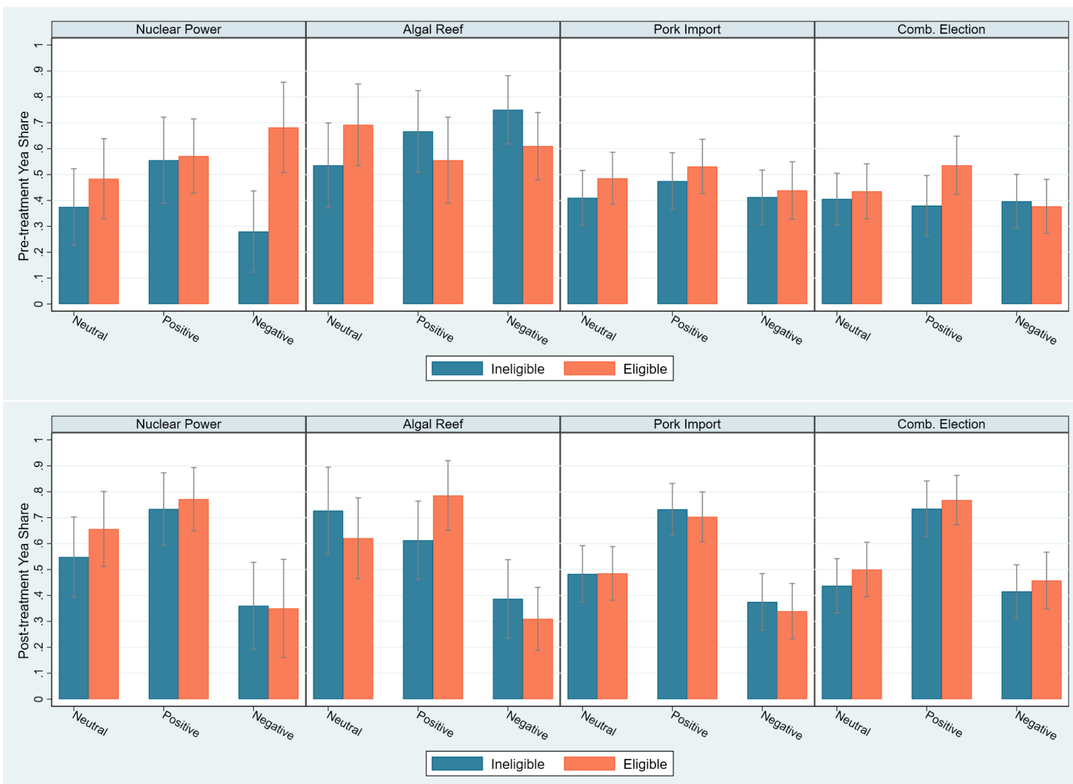



Figure 2.3: Vote shares before and after the treatments

*Notes.* The figures summarize the share of "yea" votes in each of the propositions. Observations which responded "absence" or "abstain" in the proposition are excluded. 95% confidence intervals are included.

### 2.6.2 Baseline results: Do eligible subjects react differently to the information?

We start looking at how our treatments change our subjects' voting decisions. Figure 2.4 summarizes the vote changes in each proposition, where we code a vote from "Nay" to "Yea" as 1, a vote from "Yea" to "Nay" as -1, and an unchanged vote as 0. The gap between the eligible and ineligible subjects in each treatment is the difference in the vote changes caused by the treatments. Three treatments show distinct differences: the negative treatment of *nuclear power plant*, the positive treatment of *algal reef*, and the positive treatment of *combing election and referendum*. In the first two, the eligible subjects have a larger change of voting, while in the last, the eligible subjects change less.

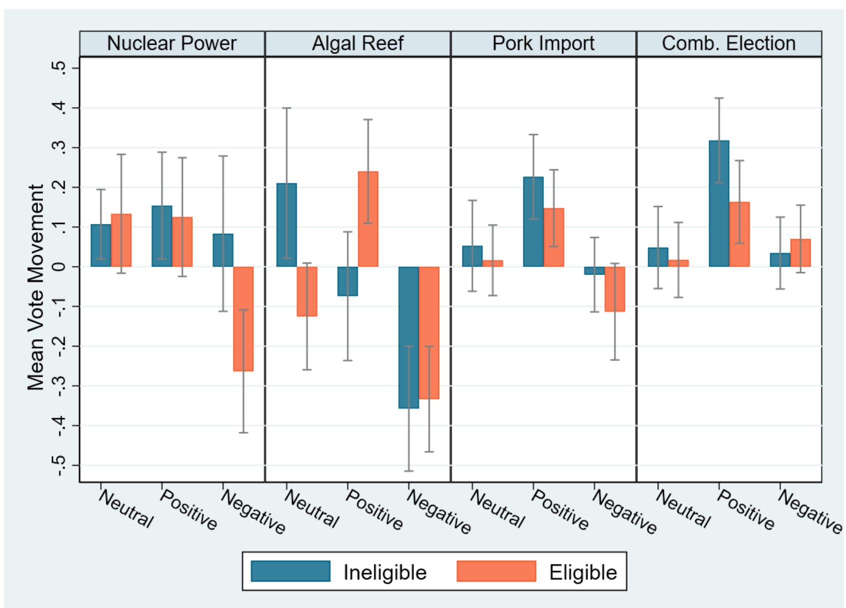



Figure 2.4: Vote Changes After Reading Treatment Articles

*Notes.* The depicted variable is the vote change. If a subject change her vote from "Nay" to "Yea", it is coded 1; if a subject change her vote from "Yea" to "Nay", it is coded -1; if a subject does not change her vote, it is coded 0. Each proposition has three treatment groups: Neutral, Positive, and Negative. In each of the treatments, the mean vote changes of ineligible and eligible subjects are depicted respectively. 95% confidence intervals are included.

We estimate the heterogeneous treatment effects in eligibility with the following regression specification.

$$\begin{aligned}\text{VoteChange}_{i,p} = \alpha + \delta\text{Eligibility}_i + \sum_{t\in T}\beta^t\text{Treatment}^t_{p,i}\\ + \sum_{t\in T}\gamma^t\left(\text{Eligibility}_i \times \text{Treatment}^t_{i,p}\right) + \varepsilon_{i,p}\end{aligned}$$

for subject $i$, proposition $p$, and treatment $t$, where the treatment is randomly drawn from $T = \{\textit{Positive, Negative}\}$ (*Control* is set as the reference group.) We can then derive the estimator in Section 2.3 First, the vote persuasion from treatment $t$ for eligible and ineligible subjects are

$$\begin{aligned}&\mathbb{E}\left[\Delta\, \textit{VoteChange}_t | \textit{Eligible}\right]\\ =&\mathbb{E}\left[\textit{VoteChange}_t | \textit{Eligible}\right] - \mathbb{E}\left[\textit{VoteChange}_c | \textit{Eligible}\right] = \beta^t + \gamma^t\\ &\mathbb{E}\left[\Delta\, \textit{VoteChange}_t | \textit{Ineligible}\right]\\ =&\mathbb{E}\left[\textit{VoteChange}_t | \textit{Ineligible}\right] - \mathbb{E}\left[\textit{VoteChange}_c | \textit{Ineligible}\right] = \beta^t\\ \Rightarrow&\mathbb{E}\left[\Delta\, \textit{VoteChange}_t | \textit{Eligible}\right] - \mathbb{E}\left[\Delta\, \textit{VoteChange}_t | \textit{Ineligible}\right] = \gamma^t.\end{aligned}$$

Hence the interaction term $\gamma^k$ is the coefficient of interest.

Table 2.5 shows the estimated results. Each column represents one proposition. We find that the negative treatment of *nuclear power plants* pushes the eligible subjects more against the proposition. We also find that the positive treatment of *algal reef* makes the eligible subjects vote more toward the proposition. Interestingly, the negative treatment of *algal reef* also caused the eligible subjects to support the proposition more. We claim this observation comes from the opposing effects of the control treatment in *algal reef*, where the control treatment increases the support of the ineligible subjects but decreases the support of the eligible ones.

We also estimate the effects without comparing with the control groups:

$$\mathbb{E}\left[VoteChange_t|Eligible\right] - \mathbb{E}\left[VoteChange_t|Ineligible\right] = \delta + \gamma^t.$$

We show the estimations beneath the main regressions in Table 2.5. We observe the same patterns we find from Figure 2.4. The eligible subjects are pushed more align with the treatments in *nuclear power plants* and *algal reef* and are pushed less with the positive treatment in *combining election*.

As the results in Table 2.5 exclude the observations of abstain votes, we also provide several alternative outcome variables. First, we elicit the subjects' potential choices by asking "if you are forced to choose either to vote 'yea' or 'nay,' how would you vote?" Then, we can find the vote change without excluding observations. The results are shown in Table D1. Second, we surveyed how much the subject supports each proposition and examined how their support changes after the treatments. The results are shown in Table D2 and Table D3, where the latter implements the standardized supports. We do not observe any qualitative change with different outcome variables.

To better interpret the results of vote changes, we further separate our sample into the original "yea" voters and "nay" voters. Figure 2.5 shows the number of subjects who switched their votes from one side to the other. The upper panel shows the original "yea" voters, where the positive treatments should stop people from changing votes, and the negative treatments should persuade people to change. We observe that the positive treatment in *algal reef* is more effective on the eligible subjects than the ineligible ones. However, in *combining election*, the positive information is less effective on the eligible subjects. The lower panel shows the original "nay" voters, and the interpretation is opposite: the positive treatments persuade and the negative treatments confirm. We

Table 2.5: Baseline Results: Voting Changes

| | *Vote Changes:* Post Vote − Pre Vote | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Nuclear Power | Algal Reef | Pork Import | Election |
| Eligible | 0.036 | -0.407$^{*}$ | -0.022 | -0.009 |
| | (0.124) | (0.157) | (0.093) | (0.096) |
| Positive Treatment | 0.035 | -0.332$^{*}$ | 0.211$^{*}$ | 0.322$^{**}$ |
| | (0.111) | (0.164) | (0.103) | (0.104) |
| Negative Treatment | 0.020 | -0.675$^{***}$ | -0.049 | 0.025 |
| | (0.145) | (0.171) | (0.098) | (0.098) |
| Eligible × Positive Treatment ($\gamma^{\text{Positive}}$) | -0.027 | 0.655$^{**}$ | -0.063 | -0.188 |
| | (0.184) | (0.206) | (0.134) | (0.144) |
| Eligible × Negative Treatment ($\gamma^{\text{Negative}}$) | -0.445$^{*}$ | 0.474$^{*}$ | -0.071 | 0.074 |
| | (0.217) | (0.215) | (0.142) | (0.129) |
| Constants | 0.195 | 0.348$^{+}$ | 0.026 | 0.109 |
| | (0.165) | (0.195) | (0.140) | (0.115) |
| Vote Change in Each Treatment Between Eligibility | | | | |
| $\delta + \gamma^{\text{Positive}}$ | 0.008 | 0.248$^{+}$ | -0.085 | -0.197$^{+}$ |
| | (0.138) | (0.135) | (0.096) | (0.106) |
| $\delta + \gamma^{\text{Negative}}$ | -0.410$^{*}$ | 0.067 | -0.092 | 0.065 |
| | (0.181) | (0.142) | (0.108) | (0.082) |
| Subjects | 151 | 160 | 325 | 319 |
| Mean of Dep. Var. | 0.079 | -0.100 | 0.052 | 0.097 |
| Pre-treatment Yea Share | 0.517 | 0.650 | 0.449 | 0.426 |
| Post-treatment Yea Share | 0.596 | 0.550 | 0.502 | 0.524 |

*Notes.* (i) Standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ (ii) *Vote Change in Each Treatment Between Eligibility* estimates (with Wald estimator) the difference in the vote changes in each treatment group between eligible and ineligible subjects. (iii) The education backgrounds (whether the subject studies at a public school, or studies social science), sex, household income, and their favorite political party are controlled.

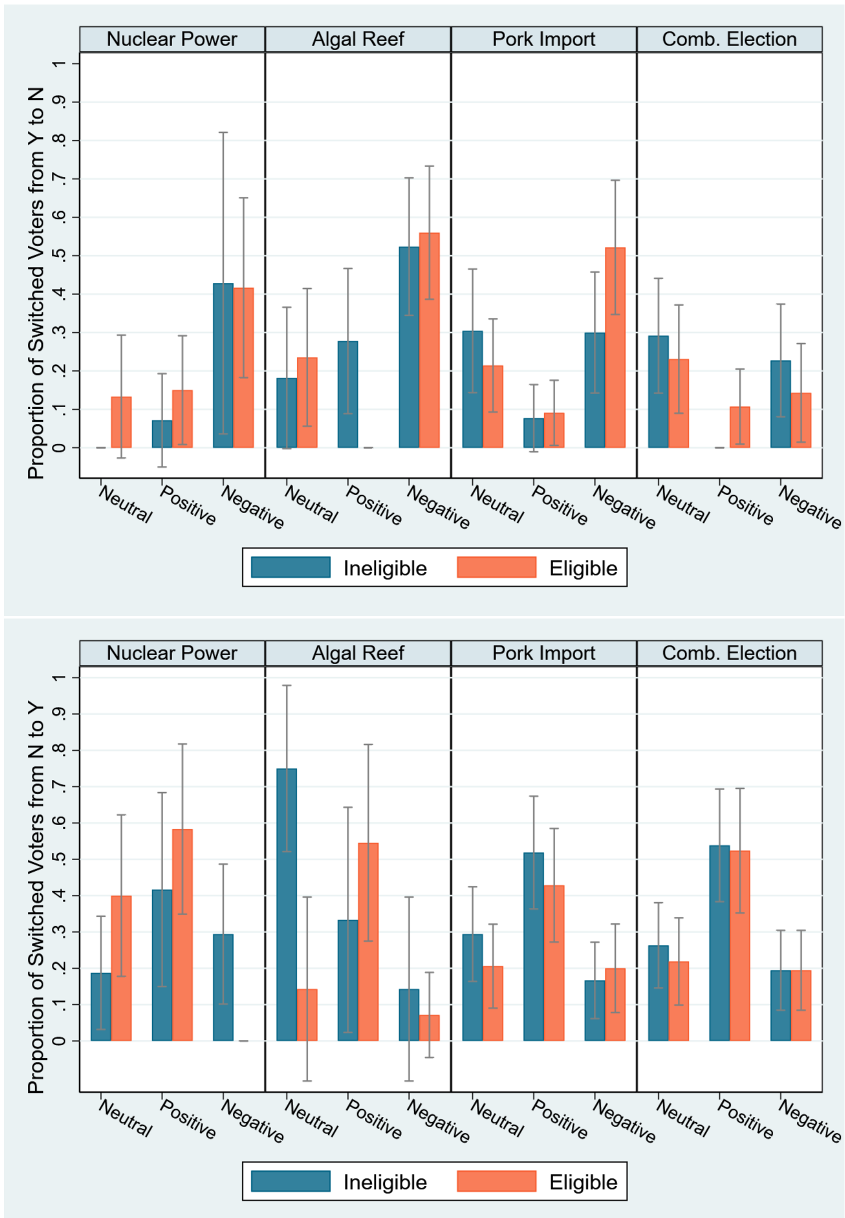



Figure 2.5: Vote Switches by Pre-treatment Votes

*Notes.* The depicted variable is the proportion of the subjects switched the vote. The upper panel includes only the original "yea" voters, and the low panel includes only the original "nay" voters. Each proposition has three treatment groups: Neutral, Positive, and Negative. 95% confidence intervals are included.

find the negative information in *nuclear power* is more effective on the eligible subjects. We also note a strong persuasion from the neutral treatment of *algal reef* on the ineligible voters.

We then provide the results of regression estimations. Table 2.6 estimates the votes changed while only including the subjects who voted "yea" in the Referendum Survey, and Table 2.7 shows the results for the subsample of the original "nay" voters. The results coincide the observations we find in Figure 2.5. Both the negative treatment in *nuclear power plant* and the positive treatment in *algal reef* make the eligible voters stick to their votes. On the other hand, the positive treatment in *combining election* make ineligible voters stick to their votes.

This separation gives us a cleaner depiction of how the treatments affect the subjects' behavior: the heterogeneity is not profound in persuasion but more distinct in stickiness. The differences in treatment effects we find between eligible and ineligible voters show that some treatments might have strong effect of confirming people's original beliefs; therefore they do not change their decisions.

### 2.6.3 Heterogeneity: Who are more easily triggered?

To explain the patterns we find in the baseline regressions, we examine the heterogeneous effects between different subgroups of subjects.

#### Environmentalist

One distinct result we find is on *opposing reopening the nuclear power plant* and *supporting algal reef protection*. Therefore, it is natural to see how the subjects' attitudes on environment would affect the heterogeneity between the eligible and ineligible subjects. Figure 2.6 depicts the subjects' pre-treatment importance evaluations of environment

Table 2.6: Voting changes of the original "yea" voters

| | *Votes Changed from "Yea" to "Nay"* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Nuclear Power | Algal Reef | Pork Import | Election |
| Eligible | 0.179 | 0.092 | -0.053 | -0.015 |
| | (0.108) | (0.164) | (0.133) | (0.138) |
| Positive Treatment | -0.079 | 0.067 | -0.176 | -0.297$^{**}$ |
| | (0.093) | (0.148) | (0.118) | (0.112) |
| Negative Treatment | 0.416$^{*}$ | 0.379$^{*}$ | -0.011 | -0.012 |
| | (0.186) | (0.174) | (0.153) | (0.153) |
| Eligible × Positive Treatment | 0.030 | -0.311 | 0.007 | 0.169 |
| | (0.154) | (0.195) | (0.156) | (0.153) |
| Eligible × Negative Treatment | -0.180 | -0.117 | 0.319 | -0.155 |
| | (0.264) | (0.237) | (0.207) | (0.182) |
| Constants | -0.112 | 0.269$^{+}$ | 0.494$^{**}$ | 0.486$^{**}$ |
| | (0.170) | (0.155) | (0.181) | (0.161) |
| Vote Change in Each Treatment Between Eligibility | | | | |
| $\delta + \gamma^{\text{Positive}}$ | 0.209 | -0.220$^{*}$ | -0.046 | 0.155$^{*}$ |
| | (0.121) | (0.107) | (0.075) | (0.076) |
| $\delta + \gamma^{\text{Negative}}$ | -0.001 | -0.026 | 0.266 | -0.170 |
| | (0.232) | (0.155) | (0.164) | (0.116) |
| Subjects | 78 | 104 | 146 | 136 |
| Mean of Dep. Var. | 0.179 | 0.327 | 0.240 | 0.169 |

*Notes.* (i) This table includes only the observations who voted yes for the proposition. (ii) Standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ (iii) *Vote Change in Each Treatment Between Eligibility* estimates (with Wald estimator) the difference in the vote changes in each treatment group between eligible and ineligible subjects. (iv) The education backgrounds (whether the subject studies at a public school, or studies social science), sex, household income, and their favorite political party are controlled.

Table 2.7: Voting changes of the original "nay" voters

| | *Votes Changed from "Nay" to "Yea"* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Nuclear Power | Algal Reef | Pork Import | Election |
| Eligible | 0.230 | $-0.713^{**}$ | -0.124 | -0.056 |
| | (0.206) | (0.236) | (0.104) | (0.118) |
| Positive Treatment | 0.252 | $-0.417^{*}$ | $0.203^{+}$ | $0.307^{*}$ |
| | (0.194) | (0.197) | (0.116) | (0.136) |
| Negative Treatment | 0.119 | $-0.703^{**}$ | -0.144 | -0.061 |
| | (0.181) | (0.247) | (0.109) | (0.108) |
| Eligible × Positive Treatment | 0.013 | $0.871^{**}$ | 0.044 | -0.001 |
| | (0.291) | (0.312) | (0.163) | (0.207) |
| Eligible × Negative Treatment | $-0.632^{*}$ | $0.706^{*}$ | 0.176 | 0.076 |
| | (0.266) | (0.328) | (0.147) | (0.153) |
| Constants | 0.141 | $0.952^{***}$ | $0.439^{**}$ | $0.465^{***}$ |
| | (0.282) | (0.247) | (0.144) | (0.136) |
| Vote Change in Each Treatment Between Eligibility | | | | |
| $\delta + \gamma^{\text{Positive}}$ | 0.243 | 0.158 | -0.080 | -0.057 |
| | (0.229) | (0.244) | (0.125) | (0.158) |
| $\delta + \gamma^{\text{Negative}}$ | $-0.402^{*}$ | -0.007 | 0.052 | 0.020 |
| | (0.177) | (0.221) | (0.107) | (0.096) |
| Subjects | 73 | 56 | 179 | 183 |
| Mean of Dep. Var. | 0.356 | 0.321 | 0.291 | 0.295 |

*Notes.* (i) This table includes only the observations who voted no against the proposition. (ii) Standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ (iii) *Vote Change in Each Treatment Between Eligibility* estimates (with Wald estimator) the difference in the vote changes in each treatment group between eligible and ineligible subjects. (iv) The education backgrounds (whether the subject studies at a public school, or studies social science), sex, household income, and their favorite political party are controlled.

issues in Taiwan. Approximately 45% of the subjects think the environment issues are extremely important. Additionally, there is no significant difference in the distribution of the importance between eligible and ineligible subjects.

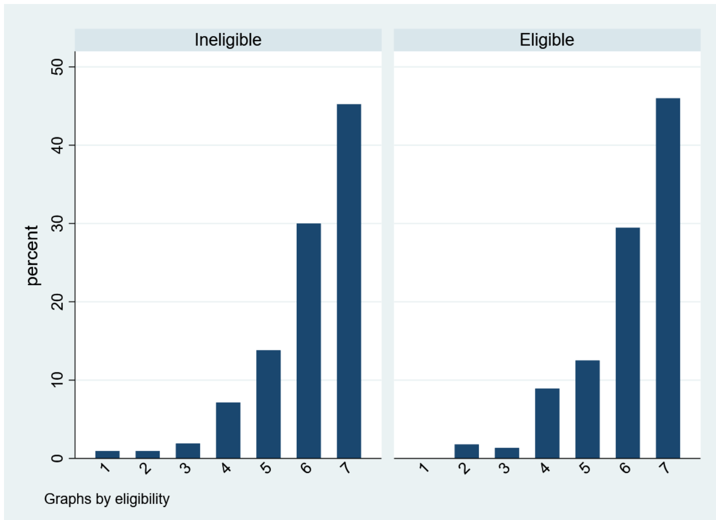



Figure 2.6: Importance of Environment Issues in Taiwan

*Notes.* The figure summarizes the response of the following question: "from 1 to 7, how important do you think the environmental issues are in Taiwan?" 1 means "not important at all", and 7 means "extremely important".

We focus on the propositions *nuclear power plant* and *algal reef*. Table 2.8 shows the results of the same regressions in the baseline results. Columns (1) and (3) include only the subjects who responded environmental issues are extremely important, and columns (2) and (4) include the remaining subjects. We find that the heterogeneity is the most distinct among the subjects who think the environmental issues are extremely important, while the subgroup not prioritizing environmental issues do not show clear heterogeneity between eligible and ineligible voters. In *algal reef*, the difference in the effect of the positive treatment is doubled when we look at only the subjects who extremely care environmental issues. This suggests that our baseline results of heterogeneous treatment effects can be partly driven by the likely-minded information. As the eligible subjects could potentially vote in the referendum, the information align with the eligible subjects' ideology may trigger their awareness of the environment and then remind them the possibility to "make a change" with the votes.

Table 2.8: Voting changes by environment cares

| | *Vote Changes:* Post Vote − Pre Vote | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Nuclear Power | Nuclear Power | Algal Reef | Algal Reef |
| Eligible | 0.284 | 0.029 | $-0.572^{*}$ | -0.412 |
| | (0.235) | (0.174) | (0.220) | (0.279) |
| Positive Treatment | 0.210 | 0.053 | $-0.523^{*}$ | -0.262 |
| | (0.195) | (0.174) | (0.232) | (0.256) |
| Negative Treatment | 0.100 | 0.072 | $-0.842^{**}$ | $-0.600^{+}$ |
| | (0.228) | (0.233) | (0.255) | (0.303) |
| Eligible × Positive Treatment | -0.337 | -0.019 | $1.040^{**}$ | $0.493^{+}$ |
| | (0.274) | (0.256) | (0.311) | (0.292) |
| Eligible × Negative Treatment | $-0.679^{+}$ | -0.282 | $0.745^{*}$ | 0.337 |
| | (0.350) | (0.291) | (0.316) | (0.371) |
| Constants | 0.265 | -0.037 | 0.045 | 0.459 |
| | (0.217) | (0.308) | (0.269) | (0.327) |
| Treatment Effect Between Eligibility | | | | |
| $\delta + \gamma^{\text{Positive}}$ | -0.053 | 0.010 | $0.468^{*}$ | 0.081 |
| | (0.213) | (0.192) | (0.216) | (0.132) |
| $\delta + \gamma^{\text{Negative}}$ | -0.396 | -0.252 | 0.172 | -0.075 |
| | (0.247) | (0.231) | (0.229) | (0.215) |
| Subjects | 70 | 81 | 83 | 77 |
| Mean of Dep. Var. | 0.100 | 0.062 | -0.096 | -0.104 |
| Pre-treatment Yea Share | 0.471 | 0.556 | 0.675 | 0.623 |
| Post-treatment Yea Share | 0.571 | 0.617 | 0.578 | 0.519 |
| Subgroup | Extremely important | Others | Extremely important | Others |

*Notes.* (i) Standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ (ii) Columns (1) and (3) include only the subsample that responded to the importance of environmental issues, and columns (2) and (4) include the rest. (iii) *Vote Change in Each Treatment Between Eligibility* estimates (with Wald estimator) the difference in the vote changes in each treatment group between eligible and ineligible subjects. (iv) The education backgrounds (whether the subject studies at a public school, or studies social science), sex, household income, and their favorite political party are controlled.

### Pre-treatment awareness and knowledge

The heterogeneity of treatment effects over eligibility can also arise from the previous awareness or knowledge of the propositions. To verify this assumption, we split the subjects at the median of their pre-treatment awareness and knowledge of each treatments. We summarize the results in Tables D4 and D5. We find the positive treatment in *algal reef* has stronger positive effects on eligible voters who were more aware of the proposition. This partly coincides with the interpretation of the "like-minded confirmation". We also observe the positive treatment in *pork import* has weaker positive effect on eligible voters who were less aware of this proposition. For pre-treatment knowledge, we do not observe specific pattern in treatment effects. With the observations, we do not conclude any pattern due to the pre-treatment awareness and knowledge.

## 2.7 Concluding Remarks

This study sheds light on the role of information in shaping political polarization, particularly among young voters. By leveraging the quasi-random treatment of eligibility in the context of the 2021 Taiwanese Referendum, we demonstrate that the first vote can affect how information influences people's voting decisions. Moreover, our findings suggest that the interaction between information and voting behavior is not uniform across all individuals but may vary based on ideological predispositions. Particularly, we observe a more pronounced heterogeneous effect among those with stronger environmental concerns, indicating that the first voting experience can serve as an active assertion of ideological identity, thereby reinforcing the impact of subsequent information exposure.

We acknowledge several limitations. Firstly, the observed heterogeneous treatment effects are not universally applicable across all treatments and propositions. This limited generalizability suggests that the impact of information on political polarization may vary depending on the nature of the information and the underlying issues at stake. Future research could explore a broader range of treatment conditions to elucidate the boundary conditions of the observed phenomenon. Secondly, while our study captures individuals' responses to treatment articles and hypothetical voting scenarios, we do not have the opportunity to track their subsequent political decisions or assess the long-term durability of the observed effects. Longitudinal data collection would enable researchers to examine the persistence of treatment effects over time and explore potential mechanisms underlying changes in political beliefs and behaviors. Furthermore, the limited sample size of our study may compromise the statistical power and robustness of our results. Although we implemented quasi-experimental identification and utilized random assignment to treatment conditions, the relatively small sample size may increase the risk of type II errors and limit the generalizability of our findings.

Overall, our research underscores the importance of considering the dynamic interplay between information, voting behavior, and ideological predispositions in understanding the mechanisms driving political polarization, particularly among young cohorts. These insights have implications for policymakers, electoral campaigns, and civic educators seeking to foster informed and engaged citizenship in an increasingly polarized political landscape.

# Chapter 3

# Preference for Sample Features and Belief Updating

*with Menglong Guan, Jing Zhou, and Ravi Vora*

## 3.1 Introduction

Different sources, such as the media, government reports, and scientific studies, often emphasize distinct statistical characteristics of the raw data about the same event, which we call sample features, to inform and influence public opinions. This requires people to interpret and incorporate the information conveyed by certain sample features for decision-making. For example, individuals who subscribe to different newspapers adjust their beliefs about a politician's favorability based on the specific statistical characteristics of the same poll results emphasized by their respective newspapers. Similarly, investors receiving financial reports from different analysts need to modify their beliefs according to the specific sample features of the same stock outcomes emphasized by the analyst whose report they receive. During the 2020 United States presidential election, some media emphasized that Biden won Georgia by a narrow margin of 0.23% (49.47% versus 49.24% between Biden and Trump), while others highlighted the significant difference in the number of votes (12,284).[1]

An important question is how people employ and perceive the usefulness of different sample features embedded in the realized signals (raw data) for belief updating, which we know surprisingly little about.[2] While there could be various reasons from the supply side as to why different sample features are adopted, it is essential to understand the demand side: Are people better at using certain features than others? Do they perceive some features as more useful than others? Are they sophisticated about their biased use, if present?

On the one hand, highlighting different sample features might not matter if people are equally good at processing each sample feature. As presumed by standard rational models, people make statistically optimal use of the information conveyed by each sample feature through Bayesian updating. On the other hand, behavioral factors can influence how effectively people use information in sample features to update their beliefs. For instance, when predicting the election winner based on a poll result, individuals could have benefited from more informative sample features, such as observing all the votes in a poll, but struggling to do so when presented with less informative alternatives, such as only knowing the relative frequency of the votes received by the poll winner.[3] For instance, if individuals know that there are 10,000 votes in total and the winner got 7000 votes, they learn that this is strong evidence indicating a high likelihood of the winner

[1]Sources: CBS News. (2020, August 6). *'Biden has edge in North Carolina and race is tight in Georgia — CBS News Battleground Tracker poll'* and Staff, A. 11Alive.com (2020, November 9). *'Blog: Joe Biden's Georgia lead widens to more than 12,000'*.

[2]While there is a large literature studying belief updating, it focuses on how people update beliefs when receiving information about the realized signals with most sample features presented (Benjamin, 2019).

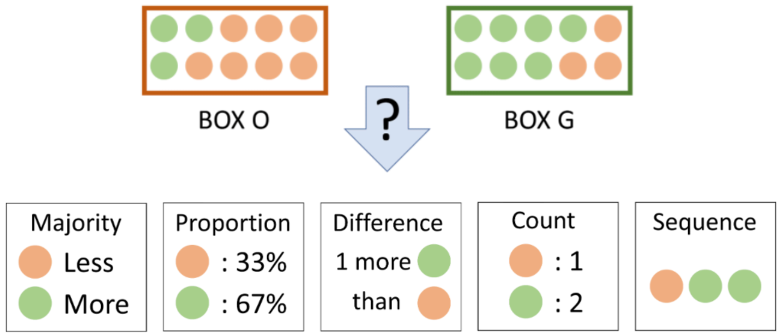
[3]The informativeness of a sample feature is defined as how much more uncertainty about the payoff-relevant state is reduced by using the sample feature to update beliefs, compared to the no-information case. See Section 3.3 for details.

winning the election as well. However, if they only know that the winner received 70% of the votes in the poll, without knowing the size of the poll, it becomes challenging to determine whether this is strong or weak evidence. Individuals must additionally account for this uncertainty when making inferences. This additional step of consideration could be cognitively taxing and affect how effectively they utilize the information.

In this chapter, we use a laboratory experiment to study these questions. Start with the widely used "balls-and-boxes" task by existing literature for studying inference from symmetric binary signals about a binary state (Benjamin, 2019), as shown in Figure 3.1. One of the two boxes is randomly selected with equal chance. Each box has ten balls, seven of which match the color of the corresponding box, while the remaining three match the color of the alternative box. That is, $\Pr(\textit{One green ball}|\textit{Box G}) = \Pr(\textit{One orange ball}|\textit{Box O}) = 70\%$. The subjects' objective is to assess the probability that the picked box is Box G versus Box O, and gets paid by Binarized Scoring Rule (Hossain and Okui, 2013). As a clue, a sequence of balls is drawn out of the chosen box with replacement. Existing studies on belief updating either use *Count* or *Sequence* ( as illustrated in Figure 3.1) to inform subjects about drawn balls.

To answer the questions of our interest, instead of directly showing the sequence of drawn balls, we propose a novel experimental design where we use five reports to separate representative sample features extracted from the information about drawn balls. The five reports are (1) *Majority*: indicates whether the set of drawn balls has more green or more orange balls; (2) *Proportion*: displays the relative frequencies of green and orange balls among the drawn balls, respectively; (3) *Difference*: demonstrates the difference in the absolute frequency of green and orange balls among the drawn balls; (4) *Count*: illustrates the absolute frequencies of green and orange balls among the drawn balls, respectively; (5) *Sequence*: depicts the original sequence in which the balls were drawn.

Among these reports, we employ *Sequence* and *Count* to replicate the findings doc-




*Note:* Existing literature studies belief updating by employing the "Balls-and-Boxes" task with *Count* or *Sequence* provided. We use a novel design by separating the sample features in *Count* into *Majority*, *Proportion*, and *Difference*.

Figure 3.1: "Balls-and-Boxes" Task and Five Sample Features

umented in the existing literature. *Sequence* contains all the sample features of the realized signals. From *Sequence* to *Count*, the information on the order of realized signals is excluded, which is not useful for Bayesian inference.[4] We use *Difference*, which is the sufficient statistics of information about realized signals for Bayesian inferences in (symmetric) inference problems (Benjamin, 2019). From *Count* to *Difference*, the information on the sample size is not provided, which is not instrumental for Bayesian inference in (symmetric) inference problems. By comparing across *Difference*, *Count* and *Sequence*, we can examine the extent to which non-instrumental features matter and how agents perceive their usefulness. We use *Proportion* to isolate the "Strength" (sample proportion) from the "Weight" (sample size), as defined in the "Strength-Weight bias" by Kahneman and Tversky (1972).[5] Without the information about "Weight," *Proportion* is

[4]Instrumental value of a report is defined as the expected payoff that a Bayesian agent can receive by using it to update beliefs in "balls-and-boxes" task, compared with the case with no information. In our setting, informativeness and instrumental value give the same prediction of the ordinal rankings among the five reports. Thus, we use informativeness (informative) and instrumental value (instrumental) interchangeably. See Section 3.3 for more details.

[5]"Strength-Weight bias" describes the bias that individuals tend to over-weight sample proportion ("Strength") while under-weighting sample size ("Weight") when using *Sequence* or *Count* to update beliefs in "balls-and-boxes" tasks. These studies exogenously manipulate sample proportion and sample size embedded in *Sequence* or *Count*, and structurally estimate the coefficients on sample size and on

less informative than *Difference*, *Count*, and *Sequence*. *Majority* is the least informative feature among the five. Comparing across *Sequence/Count/Difference*, *Proportion*, and *Majority* allows us to study how the updating behaviors respond to the change in the informativeness of sample features.

The experiment consists of two parts. Part 1 uses a ranking-cards method inspired by Dustan et al. (2022) to elicit subjects' *willingness-to-pay* of receiving each of the five reports in the "balls-and-boxes" task. It allows us to measure the perceived usefulness of each feature. In Part 2, we employ the strategy method with 33 pre-selected scenarios of the "balls-and-boxes" task. These scenarios are designed to capture how subjects respond and adjust their beliefs based on various signal realizations and different information conveyed by different reports.

We have two main findings regarding how well subjects *use* different reports when updating beliefs. These observations are robust to different measures of performance: average absolute deviation from the Bayesian benchmark and estimated responsiveness to information change using the Grether (1980) model. Firstly, subjects' belief updating deviates from the Bayesian benchmark under each report. However, it is least severe under *Proportion*, despite *Proportion* being less informative compared to *Difference*, *Count*, and *Sequence*. It suggests that subjects are better at using the "Strength"(sample proportion) when used alone, rather than when combined with "Weight"(sample size). Secondly, among the reports that are equally informative, i.e., *Difference*, *Count*, and *Sequence*, subjects' belief updating is closer to the Bayesian benchmark when using *Count* and *Sequence*, compared to *Difference*. Our findings indicate that subjects are not equally good at processing each sample feature, contrasting to what the Bayesian benchmark suggests. Moreover, the biased use does not monotonically improve with the informativeness

sample proportion, respectively. By testing whether the two coefficients are identical and equal to one, the common finding is that the coefficient on sample proportion is significantly larger than that on sample size, and both are less than one (Benjamin, 2019).

of sample features.

In terms of *perceived usefulness*, we find that, on average, the perceived usefulness of the features deviates from the predictions of instrumental value in two ways. First, there is no significant difference in the average *WTP* among *Proportion*, *Count*, and *Sequence*, despite the latter two features being more instrumentally useful than *Proportion*. Second, on average, subjects assign a significantly higher value to *Proportion/Count/Sequence* by a margin of $0.68, compared to *Difference* or *Majority*, even though the former three features have the maximum instrumental value. These results suggest that subjects fail to fully recognize the usefulness of other features, such as *Difference* and sample size, even though incorporating either of them with *Proportion* increases the instrumental value of information.

These findings suggest that subjects, on average, have a strong preference for sample features that contain *Proportion* compared to those that do not. Features that contain *Proportion*, i.e., *Count* and *Sequence*, require subjects to conduct some calculations to get the proportion information. Features that do not contain *Proportion*, i.e., *Difference* and *Majority*, require additional inference about all the potential sample proportions that could lead to the same *Difference* or *Majority* information, along with more difficult calculations. The increased difficulties of inference and calculation required to get the proportion information might lead to the distaste for *Difference* and *Majority*.

Examining the association between subjects' perceived usefulness and the actual use of the five sample features, we observe that, on average, subjects are self-consistent between their preferences and performances, making better use of the sample feature they prefer. This finding suggests that the biased use of sample features in belief updating is more likely to be an intentional deviation rather than a result of inattentive heuristics. However, there is also non-negligible inconsistency between preferences and performances, and the most prominent pattern is that some subjects prefer a report that contains more or more informative features than another but perform relatively worse under it. In each possible pairwise comparison of reports, among subjects whose preference for and performance with the two reports, a non-negligible inconsistency between preferences and performances, and the most prominent pattern is that some subjects prefer a report that contains more or more informative features than others are ordinally inconsistent, over 60% of them follow this pattern. It indicates that a significant portion of subjects tend to prioritize quantity (as many features as possible) over relevance (how useful they are in the actual task) while failing to take into account the cost of processing more features than necessary.

Our study is related to several strands of literature. First of all, our findings contribute to the existing literature on belief updating and learning. We are the first to show direct evidence of how subjects use and perceive the usefulness of sample features for belief updating. Most previous studies demonstrate the biased use of sample features based on indirect evidence and structural estimation. They identify "Strength-Weight bias" or "Sample Size Neglect," by asking subjects to update beliefs with either *Count* or *Sequence* adopted to convey the information about realized signals (Griffin and Tversky, 1992).

By estimating the coefficients on sample size and sample proportion, respectively, they find that the weight on sample size is smaller than that on sample proportion.[6] Kraemer and Weber (2004) studies how the presentation mode of the signals affects belief updating by comparing realized signals and *Proportion* plus sample size. They find that subjects' focus on sample proportion is pronounced when they receive explicit information regarding sample proportion plus sample size compared to when receiving realized signals. When most sample features are available, it is challenging to discern whether the biased weights result from the different abilities in utilizing each feature or from the inclusion of too many sample features.

[6]See Benjamin (2019) for the meta analysis.

We add to this literature by presenting direct evidence that individuals are not equally good at processing each sample feature embedded in the realized signals, and they value the usefulness of sample features differently from instrumental value. Specifically, we find that subjects are better at processing sample proportion alone, compared to more informative features or those with other features combined. Furthermore, we demonstrate that these biases are more likely to be intentional deviations rather than the result of inattentive heuristics.

Second, our study contributes to the existing literature that examines the impacts of coarse versus precise information. Ravaioli (2021) investigates how the coarsening of food labels affects the number of calories consumed in food choices. He proposes a bounded rationality model with precision overload to explain his main finding: coarse-categorical labels reduce the number of calories consumed in food choices. As a complement to his study, we provide direct evidence that, even in an abstract learning environment, individuals are worse at processing detailed information when all sample features are included, compared to coarse information with certain features excluded. We also show that not all forms of simplification work. Both *Difference* and *Proportion* contain a reduced number of sample features, yet subjects perform worse with *Difference* compared to *Proportion*, despite the former having a higher instrumental value. Our results suggest that the perceived usefulness may play a role in determining the effectiveness of coarse information: if the coarse information emphasizes a sample feature that individuals consider useful, they are more likely to make better use of it when updating their beliefs.

Third, our study is related to the demand for information literature. There is a growing literature on how people choose and evaluate information with instrumental value (Ambuehl and Li, 2018a; Charness et al., 2021; Liang, 2023; Guan et al., 2023).[7] Among

[7]There is also a large literature focusing on non-instrumental information and showing people's demand for information could be driven by timing preference of uncertainty resolution (Nielsen, 2020), preference for positive skewness (Masatlioglu et al., 2017), curiosity or motivated attention (Golman

them, the most closely related to our study is Ambuehl and Li (2018a), which connects the under-responsiveness to instrumental value in information evaluation with the non-Bayesian use of information. We also find people's evaluation of information broadly aligns with how well they use the information from the Bayesian perspective. In addition, our finding of people performing better with *Proportion* and overvaluing *Proportion* suggests that the non-Bayesian use of information could lead to more severe deviations from instrumental value than under-responsiveness in the demand for information.

The remainder of the chapter is organized as follows. Section 3.2 describes the experiment design. Section 3.3 lists theoretical predictions. Section 3.4 presents results. Section 3.5 concludes by discussing the implications of our main findings.

## 3.2 Experimental Design

We design the experiment to investigate how subjects use and perceive the usefulness of various sample features of realized signals in belief updating. To accomplish this, the experiment consists of two parts: (1) ex-ante preference elicitation; (2) belief-updating scenarios. Figure 3.2 demonstrates the experimental procedure. It starts with an introduction to the "balls-and-boxes" belief updating task, namely *Assessment Task*, and the five reports subjects may receive. This is followed by two practice rounds without feedback. Then, in Part 1, we elicit the subjects' preference regarding the five reports. In Part 2, we use the strategy method to gauge how subjects employ the information provided for belief updating across 33 pre-selected scenarios of the *Assessment Task*. Subjects face the *Assessment Task* after finishing Part 2. One of the two parts is randomly selected for payment, and subjects' decisions in the chosen part determine their final payments in the *Assessment Task*.

and Loewenstein, 2018; Golman et al., 2022), anticipatory feelings (Caplin and Leahy, 2001), etc.

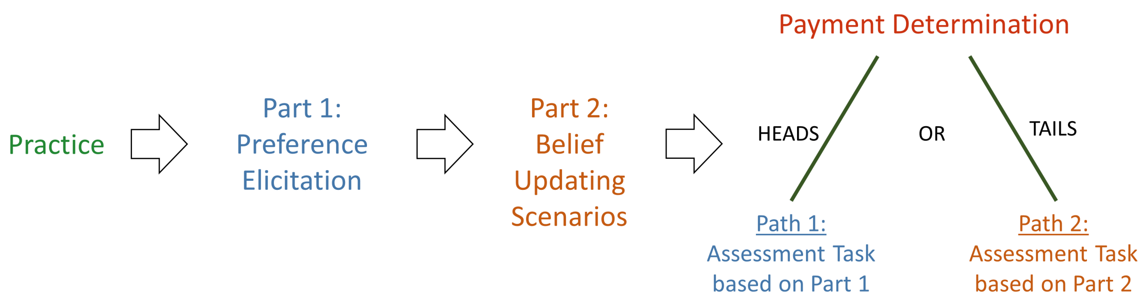



Figure 3.2: Timeline of the Experiment

The rest of this section describes the components of the experimental design in detail. First, we outline the basic setups of the belief updating task, *Assessment Task*, and the five reports of the realized signals. Then, we demonstrate how we elicit preferences regarding the five reports and performances in the belief updating scenarios. Lastly, we discuss the choices of experimental design.

## The "Assessment Task"

To measure how subjects use information to update beliefs, we use the stylized balls-and-boxes setting. This setting involves two boxes, each containing ten balls. *Box G* consists of seven green balls and three orange balls, while *Box O* consists of three green balls and seven orange balls. The computer randomly selects a box with equal probability. Thus, the state of the world $\omega$ is either $O$ or $G$. Then, the computer independently draws balls out of the chosen box with replacement.[8] Subjects do know which box is selected, and are asked to assess the likelihood of the selected box being Box O or Box G. This process of forming posterior belief is referred to as the *Assessment Task* and serves as the basis for determining the subject's likelihood of receiving the $10 bonus after completing Parts 1 and 2.

[8] Therefore, the diagnostic rate – the likelihood of drawing a ball from the box that matches the color of the box itself – is symmetric: $P(one\ green\ ball|Box\ G) = P(one\ orange\ ball|Box\ O) = 0.7$.

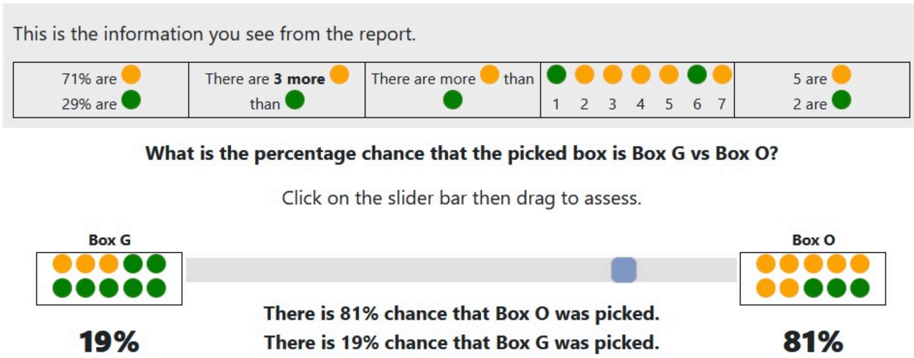



Figure 3.3: Screenshot of Assessment Task: Practice Round

The computer randomly draws $N$ balls from the chosen box with replacement, where $N$ is a random number selected from $\{3, 5, 9, 15\}$ with equal probabilities. We use $S = (s_1, \ldots, s_N)$, where for each ball, $s_n \in \{o, g\}$ with $n \in \{1, 2, ..., N\}$, to denote the sequence of drawn balls. Instead of directly observing the exact sequence of drawn balls $S$, subjects receive a summary of the sequence through one of the five reports, denoted as $\gamma_R$. The report, $\gamma_R$, maps the sequence of drawn balls ($S$) to a statistical feature of $S$ represented by report $R$, denoted as $\gamma_R(S) := S_{\gamma_R}$. Different reports capture different features of the drawn balls: (1) Sample Majority, denoted as *Majority* $\gamma_M$—"Are there more green or orange balls in the sample?"; (2) Sample Proportion, denoted as *Proportion* $\gamma_P$—"What is the fraction of green balls in the sample?"; (3) Sample Difference, denoted as *Difference* $\gamma_D$—"How many more green (orange) balls are there in the sample?"; (4) Sample Count, denoted as *Count* $\gamma_C$—"What are the total numbers of orange and green balls in the sample, respectively?"; (5) Sample Sequence, denoted as *Sequence* $\gamma_S$—"What is the sequence of drawn balls?". Figure 3.3 shows the interface of *Assessment Task* that subjects see during the practice round. Each hypothetical scenario task in Part 2, as well as the final *Assessment Task*, employs a similar interface. However, it should be noted that subjects are presented with a maximum of one report at a time.

To ensure incentive compatibility of posterior elicitation in the *Assessment Task*, we use the Paired-Uniform Scoring Method introduced in Wilson and Vespa (2018) as it elegantly sidesteps the need for detailed technical explanations.[9] Although we explain the payment determination logic to the subjects, we explicitly emphasize that it is in their best interest to report their true beliefs.

## Part 1: Preference Elicitation

Our design aims to identify both the cardinal and ordinal rankings of subjects' preferences regarding the set of reports. To achieve this, we employ a ranking-cards method whereby each subject is required to place five *Report* cards, one for each report, within an ordered list of 20 $No\ Report + Money$ cards.[10]

For the $No\ Report + Money$ cards, the dollar value ranges from \$5 to \$0, descending in increments of \$0.25. To incentivize subjects to rank the cards according to their true preferences, subjects are told that, if Part 1 is randomly chosen for payments, the computer would randomly select two cards from the set of 25. The higher-ranked card would then be designated as the report that they would receive to summarize the information about the drawn balls in the *Assessment Task*.[11]

We use the same payoff method explained previously to determine subjects' final payments based on their stated beliefs in the *Assessment Task*. If the higher-ranked card

[9]The Paired-Uniform Scoring Method is equivalent to the commonly exploited (incentive compatible) belief elicitation method, *Binary Scoring Rule (BSR)*. In the binary scoring rule, the subjects are paid according to the squared distance to the actual belief. Specifically, let $p$ be the subject's actual belief that the true state $\omega = O$ (and $1 - p$ be the belief that $\omega = G$), and $a$ be the *stated* belief. Then the subject will be informed of the realized state: when the realized state is $\omega = O$, the payoff if $1-(1-a)^2$; when when the realized state is $\omega = G$, the payoff if $1 - a^2$. Hence the expected payoff given the stated belief $a$ is $p(1 - (1 - a)^2) + (1 - p)(1 - a^2)$. One can show that the expected payoff is maximized when $a = p$.

[10]This method is incentive compatible for expected utility maximizers. See Appendix A.2 for details.

[11]For additional details about the ranking-card method and its incentive compatibility, please refer to Appendix A.2. The method is inspired by Dustan et al. (2022) but is different from theirs to some extent. In ours, subjects rank multiple object cards simultaneously, then two cards are randomly drawn and the one ranked higher is implemented. In Dustan et al. (2022), subjects insert an object card into a list of lottery cards, then a lottery card is randomly drawn. The object card will be implemented if it is ranked higher than the drawn lottery card; otherwise, the lottery card is implemented.

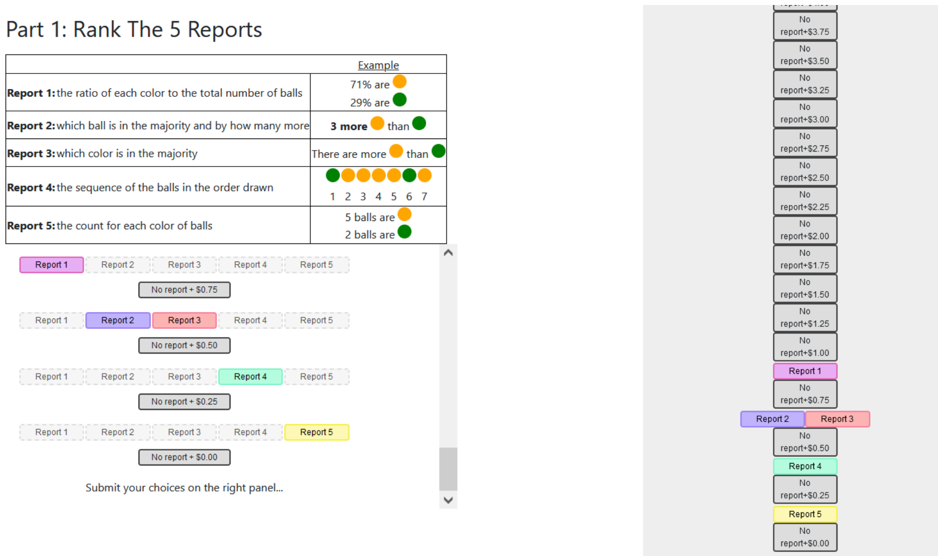



Figure 3.4: Screenshot of Ranking-Card Preference Elicitation Over Reports

is a *Report* card, denoted as $\gamma_R$, subjects will complete the *Assessment Task* with the information about the drawn balls summarized by the corresponding report, $S_{\gamma_R}$. On the other hand, if the higher-ranked card is a $No\ Report + Money$ card, subjects will finish the *Assessment Task* without any information about the drawn balls. In addition to the payment received from the task, they will also receive the monetary compensation specified on the card. Figure 3.5 depicts an example of the *Assessment Task* when Part 1 is selected for payment and the $No\ Report + Money$ card is ranked higher.

## Part 2: Belief Updating Scenarios

We employ the strategy method to measure subjects' performances across 33 pre-selected scenarios of the *Assessment Task*. To be more specific, after subjects state their preferences for the five reports, they proceed to complete the hypothetical *Assessment Task* for the set of 33 predetermined scenarios. Figure 3.6 is an example of it.

In each scenario, subjects are presented with one report and are asked to state their posterior beliefs. If Part 2 is selected for payments, in the *Assessment Task*, the computer

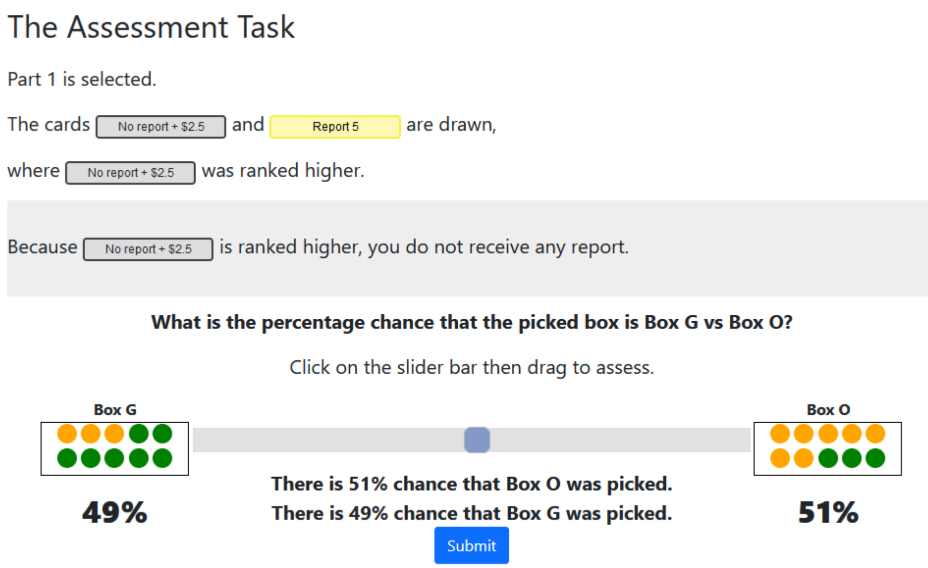



Figure 3.5: Screenshot of the *Assessment Task* when Part 1 is Selected for Payment

will check whether the information about the drawn balls, as summarized by report $R$ ($S_{\gamma_R}$), matches one of the pre-selected scenarios. If a match is found, the computer will utilize the subjects' stated beliefs from that specific scenario as their posteriors in the *Assessment Task*, to determine their final payments. If there is no match with any pre-selected scenario, subjects need to manually complete the *Assessment Task* by reporting their beliefs via the slider bar. Consequently, subjects have no incentive to provide false posteriors beliefs during Part 2.

## Understanding the Design

We design the experiment to answer two questions: (1) how subjects use different sample features embedded in the realized signals when updating beliefs; and (2) how they perceive the usefulness of the sample features in helping belief updating. Here we highlight the design choices made to facilitate these goals.

First, to cleanly identify how subjects use the sample features embedded in the re-

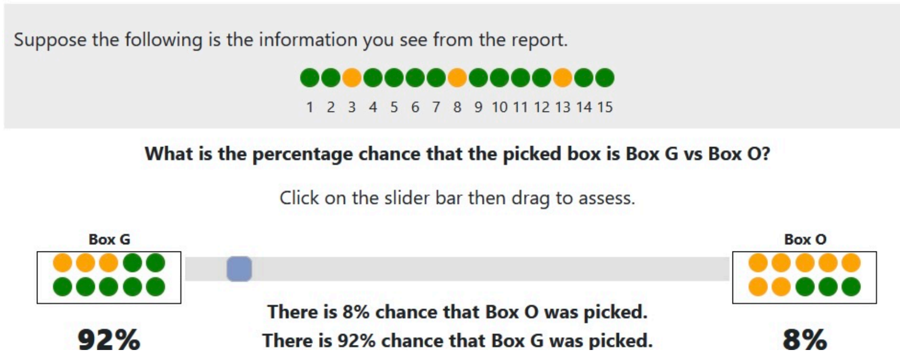



Figure 3.6: Example of a Scenario in Part 2

alized signals, we employ the classical "balls-and-boxes" setting with symmetric prior ($\Pr(Box\ G) = \Pr(Box\ O) = 50\%$) and symmetric diagnostic rate ($\Pr(1\ green\ ball|Box\ G)$ $= \Pr(1\ orange\ ball|Box\ O) = 70\%$). The use of symmetric prior and symmetric diagnostic rate serves two purposes in our study. Firstly, it reduces the burden of understanding the belief updating environment, making it easier for participants to comprehend and engage with the task. Secondly, it helps mitigate any potential bias that could arise from suboptimal utilization of prior information or an asymmetric perception of diagnostic rates. By employing symmetric priors and diagnostic rates, we aim to minimize any distortions in our objective of identifying how subjects utilize the sample features, ensuring a more accurate analysis.[12]

Second, we carefully choose five reports to capture representative sample features. Firstly, we use *Count* and *Sequence* as benchmarks to replicate findings from existing literature on belief updating (Benjamin, 2019). Secondly, we employ *Proportion*, which indicates the "Strength" (representativeness of the signals) in the "Strength-Weight bias" or "Sample Size Neglect" described by Kahneman and Tversky (1972), to isolate "Strength"

[12]We acknowledge that subjects may exhibit biases in aggregating prior information and the information of realized signals, and their use of sample features may also impact how they aggregate the information in general. Our study focuses on cleanly identifying the use of different sample features as the first step. We leave room for future extensions to explore variations such as asymmetric priors and asymmetric diagnostic rates, which could provide further insights into these phenomena.

(sample proportion) from "Weight" (sample size). Furthermore, we include *Difference*, which serves as the sufficient statistics of the information about realized signals $S$ for Bayesian inferences in (symmetric) inference problems (Benjamin, 2019).[13] By directly measuring subjects' belief updating when presented with one feature at a time, we can explore whether subjects are equally good at processing each feature but struggle when processing the information with multiple features combined. Or alternatively, their abilities to process each feature fundamentally differ and so does their perceived usefulness of each feature. This exploration may shed light on the underlying mechanisms behind biases in belief updating, such as the "Strength-Weight bias" Lastly, we employ *Majority* to maximize variations in sample features with different instrumental values. This enables us to examine the extent to which the informativeness of sample features predicts how subjects use and perceive their usefulness. For a more detailed discussion on theoretical benchmarks, please refer to Section 3.3.

Next, we intentionally select a set of 33 scenarios to achieve two goals: (1) to expose subjects to a representative range of sample outcomes for each of the five reports; and (2) to intentionally obscure the exact number of balls drawn in certain reports. Some reports require additional effort to accurately deduce the complete information about all possible realizations of drawn balls. This deliberate obscurity prompts subjects to invest thoughtful analysis in interpreting the available information, which allows us to assess the impact of inferential effort on belief updating.

Furthermore, we deliberately choose the set of numbers: $\{3, 5, 9, 15\}$, from which we sample the sample size $N$, for three reasons. Firstly, we aim to ensure that the Bayesian posteriors, as the benchmark, are uniformly distributed between 0% and 100%. To achieve this, we restrict the maximum number of balls to prevent clustering at the

[13] With asymmetric diagnostic rates, $\Pr(\textit{green ball}|\textit{Box } G) \neq \Pr(\textit{orange ball}|\textit{Box } O)$, *Difference* is still more informative than *Proportion*.

extreme values (0% or 100%). Large sample sizes could otherwise lead to near-certainty Bayesian posteriors, while very small sample sizes would result in minimal variation across reports.[14] Secondly, by selecting odd numbers as the sample size, we avoid situations where the Bayesian posterior equals the prior (50%). This enhances the statistical power of the experiment, as reports that yield 50% posteriors are interchangeable.[15] Thirdly, we select sample sizes with common factors only, with the intention of adding the needs to consider certain information can either be strong or weak evidence. This is because multiple realizations of the balls, whether it is strong or weak evidence, can map to the same information conveyed by certain report $S_{\gamma_R}$. Less informative sample features require additional steps to deal with this uncertainty which could be cognitively taxing. It allows us to investigate the extent to which this additional inferential effort predicts subjects' performance across the five reports.[16]

Finally, we have set the preference elicitation *before* the belief updating scenarios in order to understand how subjects evaluate the values of each report and predict the usefulness before experiencing the different reports in the belief update tasks. This ordering minimizes the impact of relative frequency on the evaluation, as subjects will be exposed to reports with varying frequencies during the belief updating scenarios.[17]

[14]For instance, if a subject receives a report stating "67% of balls are orange balls," having large sample sizes would lead to a near-certainty Bayesian posterior that the selected box is Box $O$ (*e.g.* a Bayesian posterior of 99.97% for $N = 30$, 98.58% for $N = 15$, and 70% for $N = 3$). With $N = 1$, the Bayesian posterior would be equal to the diagnostic rate: $\Pr(\textit{Box } G|1 \textit{ green ball}) = 70\% = \Pr(\textit{Box } O|1 \textit{ orange ball})$, resulting in minimal variation across reports.

[15]For example, *Proportion* "50% of balls are orange"— *Count* "same number of balls of different colors"— *Difference* "no difference in the number of balls of different colors" give identical Bayesian posteriors.

[16]For instance, consider the report stating "67% of drawn balls are orange." In this case, there are three equally likely scenarios with different levels of information strength: (1) a sample of two orange balls out of three draws, which would be relatively weak evidence; (2) a sample of six orange balls out of nine draws, which would be the evidence of intermediate strength; or (3) a sample of ten orange balls out of fifteen draws, which would be relatively strong evidence.

[17]By the nature of our design, there is one scenario question under *Majority* and 15 questions under *Sequence*.

# 3.3 Theoretical Predictions

In this study, we focus on two main aspects of the belief elicitation problem: the performance in the updating tasks and the preference over the reports. The following sections will describe the primary predictions of each aspect.

## 3.3.1 Performances in the Updating Task with Reports

### Setup and Bayesian Inference

We first discuss the Bayesian benchmark in the updating tasks with reports. We use $\omega \in \{O, G\}$ to denote the state of the world (which box is selected), and the objective prior belief is $\Pr(\omega = G) = \frac{1}{2}$. Given the realized state $\omega \in \{O, G\}$ (selected box), $N \in \{3, 5, 9, 15\}$ and is randomly determined with equal probability and a sequence of $N$ balls are drawn independently with replacement. The drawn sequence of balls is denoted as $S = (s_1, \ldots, s_N)$, where for each ball, $s_n \in \{o, g\}$ with $n \in \{1, 2, ..., N\}$. The diagnostic rates, probabilities that a ball $o$ is drawn from Box $O$ and a ball $g$ is drawn from Box $G$, are symmetric,

$$\Pr(s_n = o|\omega = O) = \Pr(s_n = g|\omega = G) = \theta = 0.7$$

The *Report*, $\gamma_R$, maps the sequence of drawn balls ($S$) to some statistical feature of the sample $S$ summarized by report $R$. We denote $\gamma_R(S) := S_{\gamma_R}$.[18] A Bayesian agent forms the posterior belief conditional on the feature of the drawn balls ($S$) summarized by report $R$, $S_{\gamma_R}$:

$$\frac{\Pr(O \mid S_{\gamma_R})}{\Pr(G \mid S_{\gamma_R})} = \frac{\Pr(S_{\gamma_R} \mid O)}{\Pr(S_{\gamma_R} \mid G)} \frac{\Pr(O)}{\Pr(G)} \tag{3.1}$$

where $\frac{\Pr(O)}{\Pr(G)}$ is the ratio of prior beliefs, $\frac{\Pr(S_{\gamma_R}|O)}{\Pr(S_{\gamma_R}|G)}$ is the ratio of conditional likelihood of

[18]For example, let $S = (o, o, o, g, g)$. As in our design, with *Majority*, i.e. $\gamma_M$, then $\gamma_M(S) =$ "$More\ o\ than\ g$;" with *Proportion*, i.e. $\gamma_P$ , $\gamma_P(S) =$"60% $o$ and 40% $g$."

receiving $S_{\gamma_R}$ given state, and $\frac{\Pr(O|S_{\gamma_R})}{\Pr(G|S_{\gamma_R})}$ is the ratio of posterior beliefs. With symmetric prior belief of states $O$ and $G$, the Bayesian posterior can be reduced to

$$\frac{\Pr(O \mid S_{\gamma_R})}{\Pr(G \mid S_{\gamma_R})} = \frac{\Pr(S_{\gamma_R} \mid O)}{\Pr(S_{\gamma_R} \mid G)} \tag{3.2}$$

When a Bayesian agent observes the features of $S$ summarized by reports *Sequence*, *Count*, or *Difference*, it is sufficient to use the information about the difference between the numbers of $o$ and $g$ balls in the sequence of drawn balls $S$ to find the Bayesian posterior as shown below:[19]

$$\frac{\Pr(O \mid S_{\gamma_R})}{\Pr(G \mid S_{\gamma_R})} = \frac{\Pr(S_{\gamma_R} \mid O)}{\Pr(S_{\gamma_R} \mid G)} = \frac{\begin{pmatrix} N_o + N_g \\ N_o \end{pmatrix} \theta^{N_o}(1-\theta)^{N_g}}{\begin{pmatrix} N_o + N_g \\ N_g \end{pmatrix} (1-\theta)^{N_o}\theta^{N_g}} = \left(\frac{\theta}{1-\theta}\right)^{N_o - N_g} \tag{3.3}$$

where $N_o$ and $N_g$ are the numbers of $o$ and $g$ in the sequence of drawn balls $S$, respectively. The Bayesian posterior is a function of the difference in the numbers of $o$ and $g$ balls in the drawn balls $S$, $N_o - N_g$, and the diagnostic rate, $\theta$.

For reports *Proportion* and *Majority*, however, the drawn balls with different sample size $N$ can map to the same $S_{\gamma_R}$. Thus, a Bayesian agent needs to take into account the fact that, given the realized state $\omega$, the likelihood of receiving $S_{\gamma_R}$, $\Pr(S_{\gamma_R}|Box\ \omega, N)$, varies with the number of drawn balls, $N$. For instance, when $S_{\gamma_R}$ says "33% $o$ and 67% $g$", the actual drawn sequence $S$ can be under one of the following equally-likely cases: (1) $N = 3$: 1 $o$ and 2 $g$, (2) $N = 9$: 3 $o$ and 6 $g$, or (3) $N = 15$: 5 $o$ and 10 $g$. Then, she needs to form expected likelihood of $S_{\gamma_R}$, given the realized state $\omega$, over all possible $N$.

[19] By sufficient, we mean no additional inference is needed before applying the Bayes' rule.

Thus, we further extend Equation (3.2) into

$$\frac{\Pr(O \mid S_{\gamma_R})}{\Pr(G \mid S_{\gamma_R})} = \frac{\Pr(S_{\gamma_R} \mid O)}{\Pr(S_{\gamma_R} \mid G)} = \frac{\sum_{N\in\{3,5,9,15\}} \Pr(N)\Pr(S_{\gamma_R} \mid O, N)}{\sum_{N\in\{3,5,9,15\}} \Pr(N)\Pr(S_{\gamma_R} \mid G, N)} \tag{3.4}$$

where $\Pr(N) = \frac{1}{4}$. Note that each $\Pr(S_{\gamma_R} \mid O, N)$ can be found with the same method as in Equation (3.3).

### Empirical Strategies and Hypotheses

We use two ways to evaluate how well agents use sample features when updating beliefs. On the one hand, we measure the absolute distance between agents' stated posteriors and Bayesian posteriors. For a Bayesian agent, it maximizes her expected payoff by reporting the Bayesian posteriors, and there is no difference across sample features. That is, a Bayesian agent always makes the best of each sample feature. If the stated posterior deviates less from the Bayesian posterior under one report compared to another, we say that the agent performs better under the former than the latter one.

On the other hand, we follow Grether (1980)'s framework of the balls-and-boxes paradigm to measure how responsive agents are towards the change in the likelihood ratio of receiving $S_{\gamma_R}$ given state $\omega$.[20] Grether (1980)'s framework distinguishes the biases in using realized information from those in incorporating the prior belief by adding parameters $c$ and $d$ to Equation (3.1) respectively

$$\frac{\pi(O \mid S_{\gamma_R})}{\pi(G \mid S_{\gamma_R})} = \left(\frac{\Pr(S_{\gamma_R} \mid O)}{\Pr(S_{\gamma_R} \mid G)}\right)^c \left(\frac{\Pr(O)}{\Pr(G)}\right)^d \tag{3.5}$$

where $\pi(\cdot \mid S_{\gamma_R})$ represents the subjective posterior conditional on receiving $S_{\gamma_R}$. As $\Pr(O) = \Pr(G)$ in our setting, the last term becomes 1, and therefore the subjective pos-

[20] It refers to the ratio of the likelihood of receiving $S_{\gamma_R}$ conditional on the state, $\frac{\Pr(S_{\gamma_R}|O)}{\Pr(S_{\gamma_R}|G)}$.

terior becomes a function of the likelihood ratio of the signal realizations with parameter $c$. By taking logarithm, we have

$$\ln\left(\frac{\pi(O \mid S_{\gamma_R})}{\pi(G \mid S_{\gamma_R})}\right) = c\ \ln\left(\frac{\Pr(S_{\gamma_R} \mid O)}{\Pr(S_{\gamma_R} \mid G)}\right) = c\ \ln\left(\frac{\Pr(O \mid S_{\gamma_R})}{\Pr(G \mid S_{\gamma_R})}\right) \tag{3.6}$$

where the coefficient $c$ measures how responsive agents are towards the change in the likelihood ratio of $S_{\gamma_R}$. A Bayesian agent has $c = 1$ in each report. $c < 1$ corresponds to updating as if $S_{\gamma_R}$ provided less information about the state than it actually does (under-inference). The lower the $c$, the less sensitive agents are to the change, and thus the more severe under-inference. $c > 1$ means updating as if $S_{\gamma_R}$ was more informative than it actually is (over-inference). The last equality follows from Equation (3.2). Specifically, we estimate the following regression model:

$$\ln\left(\frac{\pi(O \mid S_{\gamma_R})}{\pi(G \mid S_{\gamma_R})}\right) = a + c\ \ln\left(\frac{\Pr(O \mid S_{\gamma_R})}{\Pr(G \mid S_{\gamma_R})}\right) + \gamma\mathbf{X} + \varepsilon \tag{3.7}$$

where $\mathbf{X}$ is the vector of demographic variables added as controls; $\alpha$ is the constant term and $\epsilon$ is the residual. If the estimated $c$ from stated beliefs under some report is closer to 1 than the others, we would say that subjects perform better with the former report than the latter one.

### 3.3.2 Preference over Reports

#### Instrumental Value of Reports

We use two ways to measure the instrumental value of the reports. On the one hand, we evaluate the instrumental value of the reports by *how much the report can improve the expected payoff in the belief updating task.* Let $\mathcal{S}(\gamma_R)$ be the set of possible realizations under $\gamma_R$. As we employ the binary scoring rule (BSR) for payment, a Bayesian agent maximizes the expected payoff by reporting the Bayesian posterior given realized $S_{\gamma_R}$. Thus, the expected payoff of $\gamma_R$ is

$$\begin{aligned} &EP(\gamma_R) \\ =&B \cdot \sum_{S_{\gamma_R} \in \mathcal{S}(\gamma_R)} \left[ p(O|S_{\gamma_R})(1-(1-p(O|S_{\gamma_R}))^2) + (1-p(O|S_{\gamma_R}))(1-p(O|S_{\gamma_R})^2) \right] p(S_{\gamma_R}) \end{aligned}$$

where $B = \$10$ is the size of the bonus, and $p(S_{\gamma_R})$ is the likelihood of receiving $S_{\gamma_R}$ given $\gamma_R$. Note that without any information, the agent knows the prior only. Thus, the instrumental value is defined as the difference in the expected payoff between receiving $\gamma_R$ and receiving no information:

$$V(\gamma_R) = EP(\gamma_R) - EP(P_0)$$

where $EP(P_0)$ denotes the expected payoff without the information. In our setting, for example, the prior is $P_0 = 50\%$. So the optimal guess (50%) yields the expected payoff \$7.5:

$$EP(P_0) = 10 \times [0.5(1-(1-0.5)^2) + (1-0.5)(1-0.5^2)] = 10 \times 0.75.$$

If the agent receives report *Majority*, the information will increase the expected payoff to \$8.85. Thus the (expected) instrumental value of *Majority* is \$8.85 − \$7.5 = \$1.35.

Moreover, another widely-used measure of the usefulness of information is the reduction of the Shannon entropy (Shannon, 1948), or *informativeness* (Cabrales et al., 2013). That is, compared to the no-information case, how much more uncertainty is reduced by receiving the information about the drawn balls summarized by $\gamma_R$. Specifically, given

$\omega \in \Omega = \{O, G\}$ and the probability measure $p : \Omega \to [0, 1]$, the Shannon entropy is

$$H(p) = -\sum_{\omega \in \Omega} p(\omega) \log_2 p(\omega).$$

Let $q(S_\gamma)$ be the probability that the realized $S_{\gamma_R}$ is generated under report $\gamma_R$. Then informativeness is defined as the Shannon mutual information between prior and posterior beliefs

$$I(\gamma_R) = H(p_0) - \sum_{S_{\gamma_R} \in \mathcal{S}(\gamma_R)} q(S_{\gamma_R}) H(p_{S_{\gamma_R}}).$$

Table 3.1 demonstrates the informativeness of each report. Note that when there is no report, the informativeness is 0.

### Hypotheses

Table 3.1 summarizes the instrumental value of the five reports measured by two definitions discussed above. Note that reports *Difference*, *Count*, and *Sequence* yield the same instrumental value, which are higher than that of *Proportion*, and *Majority* has the lowest instrumental value. In addition to that, the ordinal ranking is identical between the two evaluation approaches.[21]

**Hypothesis 1.** If the agent evaluates sample features according to their instrumental value, she will rank *Difference/Count/Sequence* as the most preferred features, *Majority* as the least preferred features, and *Proportion* as somewhere in between.

Based on the discussion above, we can identify two categories of comparisons among reports. The first category focuses on reports that have maximum instrumental value and yield identical Bayesian posteriors, namely *Difference*, *Count*, and *Sequence*. Each of

[21] Thus, given our theoretical benchmark, we use the terms informativeness (informative) and instrumental value (instrumentally valuable) interchangeably, which captures the level of uncertainty on the information accuracy.

Table 3.1: Two Measures of the Value of Reports

| | No Report | Majority | Proportion | Difference/Count/Sequence |
|---|---|---|---|---|
| Instrumental Value $V(\gamma_R)$ | \$0 | \$1.35 | \$1.46 | \$1.52 |
| Informativeness $I(\gamma_R)$ | 0 | 0.44 | 0.51 | 0.55 |

*Note:* The instrumental value of each report is the difference in the expected payoff between between each report and no report. The informativeness of each report is the reduction of the Shannon entropy compared to the no-report case.

them aggregates the information of the drawn balls, $S$, in a lossless way. When facing any of them, a Bayesian agent uses the information on the difference in counts of different-colored balls to derive Bayesian posterior. *Count*, in addition to providing difference information, also conveys the sample size of $S$. *Sequence*, on top of counts, provides the information about the order in which the balls in $S$ were drawn.[22] However, neither sample size nor order is necessary for Bayesian inference. The theoretical benchmark suggests that, given the drawn balls $S$, the Bayesian posteriors should be identical across *Difference*, *Count*, and *Sequence*. Any deviation in performance or evaluation implies that the agent might use or perceive the usefulness of the non-instrumental feature(s) in a non-standard manner.

The second category focuses on reports that *differ* in their informativeness, with the three reports mentioned in the first category being more informative than *Proportion*, while *Proportion* is more informative than *Majority*. Less informative reports require agents to additionally take into account that the information can be either strong evidence or weak evidence. For example, when receiving "two orange balls and 1 green ball are drawn out of the selected box", agents can learn this is a relatively weak evidence. On the contrary, consider the previous example of the report stating "67% of drawn balls

[22]Given symmetric diagnostic rates, reports *Difference*, *Count*, or *Sequence* of the drawn balls $S$ give the same Bayesian posterior. With asymmetric diagnostic rates, *Difference* is no longer a sufficient statistics of the drawn balls $S$ but still has a larger instrumental value than those processed by *Proportion* and *Majority*.

are orange." Agents need to take into account that three equally likely scenarios with different levels of information strength could give the same information: (1) a sample of two orange balls out of three draws, which would be relatively weak evidence; (2) a sample of six orange balls out of nine draws, which would be the evidence of intermediate strength; or (3) a sample of ten orange balls out of fifteen draws, which would be relatively strong evidence. The additional inference required by less informative reports might be cognitively demanding, which could result in larger deviation.[23] By comparing whether the performance ranking is in line with the ranking of instrumental value, we can test whether this additional inferential effort predicts how well subjects use the sample feature for belief updating.

Lastly, if agents are sophisticated about how well they will use the sample features to update beliefs, their preference would be consistent with performance.

**Hypothesis 2.** If the agent is sophisticated about how she would use each sample feature for belief updating, her perceived usefulness would be consistent with how she actual uses sample features.

## 3.4 Results

We organize our main results as follows: Section 3.4.1 documents how subjects update their beliefs using the information provided by the five reports.[24] In Section 3.4.2, we compare the average willingness to pay to assess how subjects perceive the usefulness of each report. Section 3.4.3 explores the relationship between the actual use and perceived usefulness of the five reports.

[23] Studies on uncertainty in signal interpretation find that individuals tend to be more conservative or insensitive to information change when they are uncertain whether the signal is strong or weak evidence (compound diagnostic rate) (Liang, 2021; Epstein et al., 2019).

[24] We employ the terms "report" and "sample feature" interchangeably in this paper to refer to the same concept.

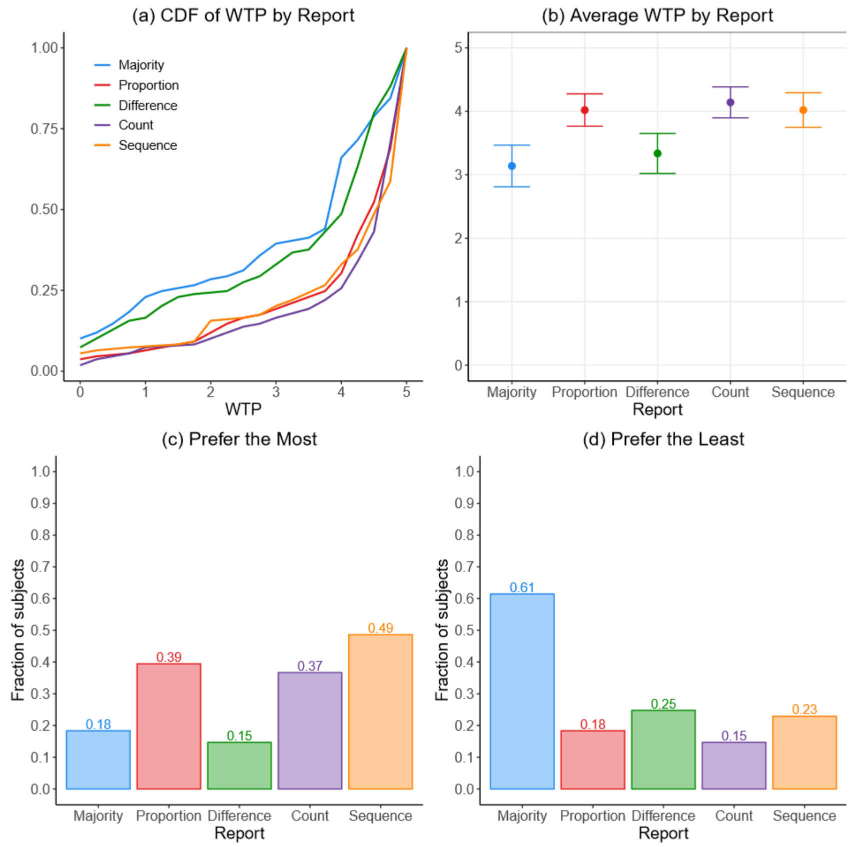
### 3.4.1 Performances across Sample Features

We apply two measures to assess the effectiveness of subjects in utilizing the information provided by each of the five reports when updating their beliefs.

First of all, we calculate the average absolute deviation from the Bayesian benchmark using subjects' stated beliefs, and compare them across the five reports. Figure 3.7 depicts the average absolute deviation for each report. We observe that subjects exhibit the least deviation under *Proportion*. It is significantly smaller than the deviations under *Count* and *Sequence* (t-test for each pairwise comparison, $p < 0.01$), even though the latter two are more informative than *Proportion*. The deviation under *Difference* is significantly larger than those observed in *Count* and *Sequence* (t-test for each pairwise comparison, $p < 0.01$), despite the three of them being equally informative. The largest deviation occurs under *Majority*, which are significantly larger than the deviations observed in the other reports (t-test for each pairwise comparison, $p < 0.01$). This finding provides evidence against the hypothesis that the extent to which subjects deviate from the Bayesian benchmark is identical across reports. Moreover, the observed difference in performance cannot be fully explained by variations in the informativeness of the five sample features.

In addition, we use the Grether model as an alternative measure to assess performance. This model allows us to estimate the responsiveness of subjects to changes in the likelihood ratio based on the information presented in each of the five reports. Figure G1 plots the average stated beliefs against the corresponding Bayesian posteriors for each report.[25] A Bayesian agent would consistently state their subjective beliefs as the Bayesian posteriors, resulting in a 45-degree line.

[25] The stated beliefs of 0% and 100% are excluded from Figure G1 and Table 3.2 due to the logarithmic property used in the calculations. For the complete data, including these extreme beliefs, please refer to Appendix G., where we apply a linear approximation to accommodate the stated beliefs of 0% and 100%.




*Note:* The figure depicts the mean deviation of the subjects' beliefs from the Bayesian posterior (in percentage term). For instance, if a subject assesses a belief of 80% against a scenario with the Bayesian posterior of 85%, the deviation is 5. 95% confidence intervals are included.

Figure 3.7: Average Deviation from Bayesian Benchmark by Report

Remarkably, Figure G1 demonstrates that the widely-established inverse S-shaped relationship between average stated beliefs and Bayesian posteriors, commonly observed in canonical "ball-and-box" belief updating tasks, is present across all five reports. The stated beliefs tend to be compressed closer to the 50:50 rather than aligning with the 45-degree line. This suggests that under-inference, under-reaction to changes in the likelihood ratio, exists across all five reports. More importantly, the stated beliefs are closest to the 45-degree line under *Proportion*, indicating that subjects are the most responsive to changes in the likelihood ratio under *Proportion* compared to other sample features.

To formalize this, we estimate the coefficient of the reduced-form model proposed by Grether (1980), as shown in Equation (3.7), for each of the five sample features. Table 3.2 presents the estimated $c$ for each sample feature. Firstly, our results replicate previous findings where subjects receive *Count* or *Sequence* as signals. Specifically, in line with Benjamin (2019), we find that the estimated coefficients under *Count* and *Sequence* are 0.356 and 0.364, respectively.[26]

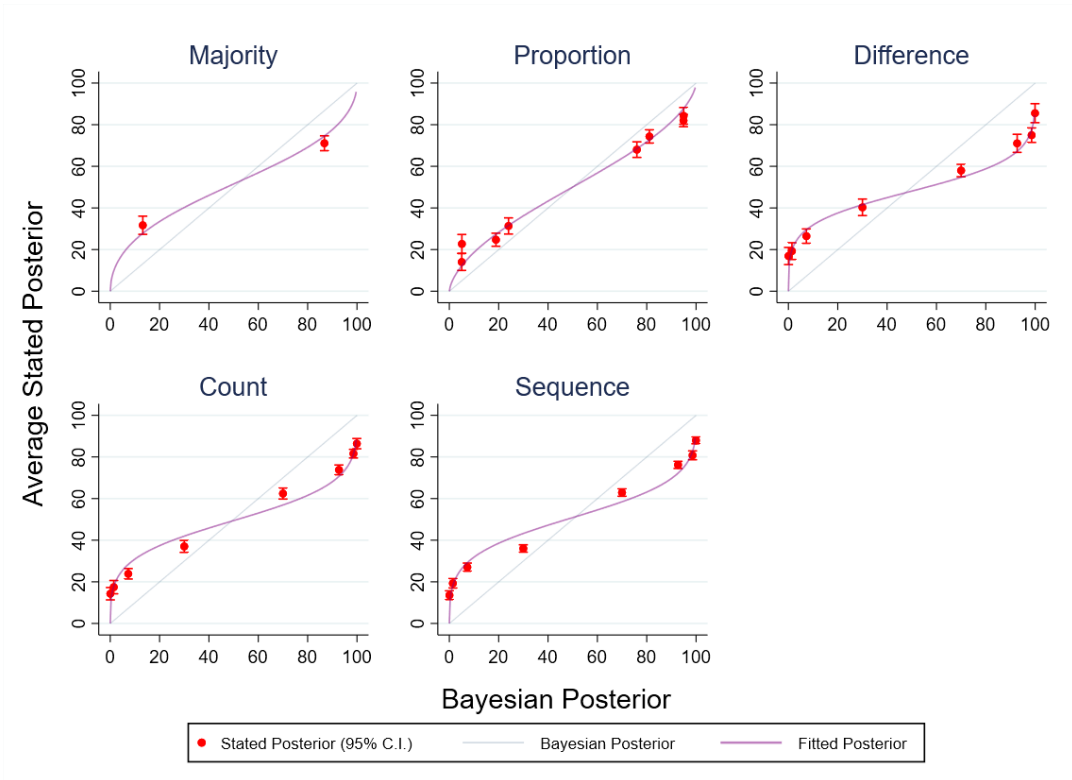
Notably, as shown in Table 3.2, our study is the first to estimate $c$ specifically for *Proportion* and *Difference*, and find them to be 0.679 and 0.311 separately. With a pooled analysis that combines all the observations and includes interaction terms for each sample feature, we find that the estimated $c$ under *Proportion* is closer to 1 and significantly larger than any other sample feature (t-test for each pairwise comparison, $p < 0.01$). It indicates that subjects are more responsive to changes in the information conveyed by *Proportion* compared to the other features.[27] The estimated $c$ for *Difference* is significantly smaller than that for *Count* and *Sequence* separately (t-test for each pairwise comparison, $p < 0.01$). This implies that subjects are less sensitive to changes in the likelihood ratio when using *Difference*, despite it being equally informative as *Count* and *Sequence*.[28][29] By

[26] In his meta-analysis, Benjamin uses the data from previous literature, where participants receive *Count* or *Sequence* as signals and elicit their beliefs to study belief updating. He finds that the estimated coefficient of $c$ is 0.383 with a standard error of 0.028.

[27] See Appendix G. for more details.

[28] Due to the limited number of observations available for *Majority*, we are cautious in drawing conclusions about subjects' responsiveness to information changes under *Majority*. Each subject only receives one information under *Majority*, either indicating more orange or more green balls. Therefore, we acknowledge the need for further investigation and caution in interpreting the results regarding subjects' responsiveness to information changes under *Majority*.

[29] One potential explanation for the subjects' improved performance under *Proportion* is that subjects may naively report the observed proportion information as their stated beliefs, resulting in a higher estimated $c$. To test this hypothesis, we categorize the stated beliefs into two groups: beliefs within a 5% range of the sample proportion and beliefs outside of this range. We find that 67% of the stated beliefs fall *outside* of the 5% range of the sample proportion. Moreover, when we plot the stated beliefs against the corresponding Bayesian posteriors, separating them by the two groups, the stated beliefs *outside* of the 5% range of the sample proportion are closer to the Bayesian benchmark than to the 50:50. This suggests that the improved performance under *Proportion* is not solely driven by a naive




*Note:* The stated posteriors are plotted against Bayesian posteriors and separated by reports. On each point, we plot the 95% confidence interval. The blue lines represent the 45-degree line, which denotes the Bayesian benchmark. The fitted posterior is derived from Equation (3.7) with the coefficients from Table 3.2. On the fitted lines, the stated beliefs of 0% and 100% are excluded due to the property of taking logarithm.

Figure 3.8: Underinference of Information by Report

measuring subjects' responsiveness to changes in the likelihood ratio, we observe similar patterns as with the average absolute deviation from the Bayesian benchmark: subjects are not equally responsive to the information change across the five reports, and this variation does not respond to increasing the informativeness of the five reports.

We summarize these results as follows:

**Result 4.** *Subjects' belief updating is the closest to Bayesian benchmark when using Proportion, despite Proportion being less informative compared to Difference, Count, and*

reporting of the observed proportion information. Please see Appendix G.1 for more details.

Table 3.2: Effect of Information Strength on Under-inference by Report

| | (1) Majority | (2) Proportion | (3) Difference | (4) Count | (5) Sequence | (6) All |
|---|---|---|---|---|---|---|
| $\ln\left(\frac{p(O\|S_{\gamma_R})}{p(G\|S_{\gamma_R})}\right)$ | 0.535*** | 0.679*** | 0.311*** | 0.356*** | 0.364*** | 0.367*** |
| | (0.0565) | (0.0325) | (0.0183) | (0.0169) | (0.0158) | (0.0159) |
| Constant | 0.0967 | -0.228* | -0.174* | -0.186** | -0.0339 | -0.0934 |
| | (0.194) | (0.124) | (0.104) | (0.0841) | (0.0707) | (0.0706) |
| Observations | 97 | 390 | 387 | 856 | 1475 | 3205 |

*Note:* We calculate the ratio of stated posteriors and then take the natural log to form the explained variable, $ln\left(\frac{\pi(O|S_{\gamma_R})}{\pi(G|S_{\gamma_R})}\right)$. For the explanatory variable, we calculate the ratio of Bayesian posteriors and then take the natural log, $ln\left(\frac{p(O|S_{\gamma_R})}{p(G|S_{\gamma_R})}\right)$. The observations with $\pi(G|S_{\gamma_R}) = 0$ or 1 are dropped. Columns (1) - (5) represent the regression estimations under each of the five reports, respectively. Column (6) indicates the regression results with all the data pooled together. Two categorical variables, gender and grades, are added as controls in all the regressions. Standard errors are clustered at the subject level and presented in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

*Sequence. Moreover, among the sample features that are equally informative (Difference, Count, and Sequence), subjects' belief updating is closer to the Bayesian benchmark under Count and Sequence than under Difference.*

Our findings suggest that, different from the Bayesian benchmark, subjects do not exhibit equal proficiency in utilizing the various sample features in the realized signals for belief updating. Additionally, the performances do not respond to the informativeness of sample features in two ways: (1) subjects' performances do not monotonically improve with the informativeness of the features provided in the reports: they are better at using *Proportion* compared to other features with higher instrumental value, namely *Count*/*Sequence*/*Difference*. (2) some non-instrumental feature helps: when comparing *Difference*, *Count*, and *Sequence*, subjects are better at using *Count* and *Sequence*, even though these additional features do not add more instrumental value for Bayesian inference compared to *Difference*. Our results also shed light on the "Strength-Weigh bias" by suggesting that subjects exhibit better performance in utilizing the "Strength" (sample proportion) when used independently, rather than when combined with "Weigh" (sample size).

Furthermore, the varying difficulties associated with retrieving proportion information from the received reports could explain the differences in belief updating performances across the reports. On the one hand, when facing *Count* and *Sequence*, subjects may need to conduct additional mental calculation to extract the proportion information. This computational burden could tax subjects' belief updating behaviors, resulting in a compression towards 50:50 and reduced sensitivity to changes in the likelihood ratio.

On the other hand, retrieving the proportion information under *Majority* and *Difference* requires additional inference about all possible proportions that could yield the same information. This additional step of inference may result in less effective utilization of the information when updating beliefs.

Last but not least, the observation that the deviations under *Count* and *Sequence* are smaller compared to those under *Difference* and *Majority* suggests that the complexity associated with making inferences may be greater than that of performing calculations. However, it is important to note that these arguments assume that subjects perceive *Proportion* as the most useful feature for belief updating and would like to extract it from received reports. We provide further support for this assumption in the next section.

### 3.4.2 Preferences across Sample Features

In this section, we explore subjects' perceived usefulness of the five reports by assessing their elicited willingness to pay ($WTP$), and compare it with theoretical predictions of instrumental value.

Panel (a) of Figure 3.9 depicts the distribution of $WTP$ for each report. The distributions of *Proportion*, *Count* or *Sequence* first order stochastically dominate those of *Majority* or *Difference*. Panel (b) of Figure 3.9 shows the average $WTP$ for each report. There is no significant difference in the average $WTP$ among *Proportion*, *Count* and *Sequence*. The average willingness to pay for *Difference* is also lower than that for *Proportion* by \$0.68. Between *Proportion* and *Difference*, approximately 65% of subjects express a preference for the former over the latter. Our results indicate that subjects prefer *Proportion*, *Count* and *Sequence* the most, while preferring *Majority* the least, and *Difference* is somewhere in between.[30]

To test the extent to which the gap in $WTP$ is driven by different monetary scales subjects use for evaluation, Panels (c) and (d) of Figure 3.9 plot the fraction of subjects who consider each report as the most preferred and the least preferred, respectively. We find that the gap observed in average $WTP$ is not solely due to different scales that subjects use to rank reports. The ordinal ranking demonstrates a consistent pattern: the majority of subjects rank *Proportion*, *Count*, and *Sequence* as the most preferred reports, while ranking *Majority* and *Difference* as the least preferred reports.

In addition, there exists notable heterogeneity in the perceived usefulness of reports containing information about sample proportion, namely *Proportion*, *Count* and *Sequence*. Some subjects prioritize receiving the sample proportion only, while others recognize the value of incorporating additional features. Among the subjects, 39% rank *Proportion* as the most preferred report, while 37% and 49% rank *Count* and *Sequence* as the most preferred, respectively. Subjects who rank *Proportion* highest are willing to pay an average of \$1.17 more to avoid receiving additional features beyond sample proportion. On the other hand, those who rank *Count* or *Sequence* as the most preferred

[30]Pairwise Wilcoxon rank test on ranking with multiple testing correction (Benjamini-Hochberg adjustment) suggests that the gap of $WTP$ between *Proportion*/*Count*/*Sequence* and *Difference* is significant at 99% confidence level, and the difference between *Difference* and *Majority* is significant at 90% of the confidence level.

report appreciate the values of the extra features alongside sample proportion, as indicated by their willingness to pay an average of \$0.66 more to receive *Count* or *Sequence*, compared to *Proportion*.

In sum,

**Result 5.** *The preference for sample features deviates from instrumental value in two ways:*

1. *On average, subjects consider Proportion, Count and Sequence as equally useful, despite the features in the latter two being more informative than Proportion;*

2. *Subjects, on average, value Count and Sequence more than Difference, even though all three are equally informative for Bayesian inference.*

Our findings suggest that subjects' perceived usefulness of sample features does not align with their instrumental value. On average, the subjects have a strong preference for reports that contain the feature of sample proportion compared to those that do not. However, they fail to fully recognize the usefulness of other features such as sample difference and sample size, even though incorporating the latter two with *Proportion* makes the information more useful for Bayesian inference.

These findings suggest that subjects, on average, have a stronger preference for sample features that contain *Proportion* compared to those that do not. Features that contain *Proportion* (*Count* and *Sequence*), require subjects to conduct some calculations to get the proportion information. Features that do not contain *Proportion* (*Difference* and *Majority*), require additional inference about all the potential sample proportions that could lead to the same difference or majority information. It is noteworthy that there are differences in the degree of aversions towards these two types of additional efforts. Subjects demonstrate a stronger aversion (higher $WTP$) to avoid the need to make additional inferences compared to the need to perform additional calculations. This suggests that subjects may perceive the former as more difficult than the latter.

The observed heterogeneity in the perceived usefulness of reports containing the sample proportion indicates a potential variation in the relationship between individual preferences and performances. Some subjects exhibit a “Strength-Weight preference” by preferring *Proportion* the most, while others prioritize reports that have sample size along with *Proportion*. These findings suggest that there might be some heterogeneity in the association between preferences and performances, which we will discuss in detail in the next section.

### 3.4.3 Association between Preferences and Performances

In this section, we aim to examine the association between subjects’ perceived usefulness and their actual use of the five reports. We investigate whether subjects who underestimate the usefulness of certain features also tend to use them suboptimally. By analyzing this association, we can gain valuable insights into the nature of deviations from the Bayesian benchmark, distinguishing between intentional deviation and inattentive heuristics.

On the one hand, if subjects’ preferences align with their performance, it would suggest that subjects have a sophisticated understanding of the usefulness of each report for belief updating. Consequently, the observed non-standard belief updating would likely be an intentional deviation from the Bayesian approach. On the other hand, if subjects’ preferences are inconsistent with their performance, it would indicate that subjects fail to accurately predict their performance. Other behavioral traits might affect how they value information as well. In such cases, the non-standard belief updating is more likely to be a result of inattentive heuristics.

To achieve this goal, we measure each subject's performance across the five reports by calculating their average absolute deviation for each report. We use each subject's $WTP$ values for the five reports to measure subject-level preference, and use the ten pairwise comparisons to calibrate the complete relationship among the five reports. We employ regression estimation to formalize the relation between preference and performance. The dependent variable is the difference in the average absolute deviation between Report $X$ and Report $Y$, for each pair of reports. We construct a categorical variable to capture the relative comparison between $WTP_X$ and $WTP_Y$, which serves as the explanatory variable. We also use the indicator variable on whether the average absolute deviation under Report $X$ is smaller than that under Report $Y$ as an alternative dependent variable. It helps determine whether subjects are more likely to perform better (indicated by a smaller deviation) under one report compared to the other.

Table 3.3 demonstrates the main regression results. Compared to the case of indifference ($WTP_X = WTP_Y$), subjects deviate 3.28 less under the more-preferred report than under the less-preferred one. Going by one category of the pairwise comparison outcomes between $X$ and $Y$ (*e.g.*, from indifference to preferring $X$ over $Y$) is associated with an increase of 66% ($e^0.508 - 1 \approx 0.66$), in the likelihood of deviating less in $X$ compared to $Y$. Both results are statistically significant at the 95% confidence level. These findings indicate that, on average, subjects are consistent between preferences and performances: they perform better under the report they prefer.

We use the ordinal rankings of both preference and performance to explore the heterogeneity of the preference-performance relationship. To be more specific, we rank the five reports based on the number of sample features they contain or the level of informativeness of those features. According to this criterion, the ranking of reports is as follows: $1^{st}$ *Sequence*, $2^{nd}$ *Count*, $3^{rd}$ *Difference*, $4^{th}$ *Proportion*, and $5^{th}$ *Majority*.

For each pair of reports, we refer to the one ranked lower on this list as Report $X$

Table 3.3: Association between Preference and Performance

| | (1) | (2) |
|---|---|---|
| | $AD_X - AD_Y$ | $\mathbf{1}\{Perform\ Better\ in\ \mathrm{X}\}$ |
| $WTP_X > WTP_Y$ | -3.279 ** | 0.508 ** |
| | (1.506) | (0.221) |
| $WTP_Y > WTP_X$ | -0.496 | -0.225 |
| | (1.467) | (0.218) |
| (Intercept) | 2.348 * | -0.145 |
| | (1.405) | (0.182) |
| N | 1090 | 1090 |
| (Pseudo) $R^2$ | 0.024 | 0.034 |

*Note:* In Column (1), the dependent variable is the difference in the average absolute deviation from Bayesian posterior between Reports $X$ and $Y$ in a given pair. We construct a categorical variable that takes the value of 1, 0, or -1 if $WTP_X > WTP_Y$, $WTP_X = WTP_Y$, or $WTP_X < WTP_Y$, respectively, to be the independent variable. In Column (2), we use Logit model and the indicator variable on whether the average absolute deviation under Report $X$ is smaller than Report $Y$ as an alternative dependent variable to capture whether subjects are more likely to perform better (smaller deviation) under one report versus the other. Standard errors are clustered at the subject level and presented in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

and the alternative as Report $Y$. Within each pair of reports, we define a preference-performance relation as “Perform better under Preferred” if a subject exhibits a smaller average absolute deviation ($AAD$) and states a larger $WTP$ for one report compared to the alternative in that pair. In addition, we consider a preference-performance relation type as “Prefer more but better with less” if a subject has a smaller $AAD$ but states a lower $WTP$ on Report $Y$ compared to Report $X$. On the other hand, a preference-performance relation is categorized as “Prefer less but better with more” if a subject has a larger $AAD$ but states a larger $WTP$ on Report $Y$ compared to Report $X$. Table 3.4 illustrates the definition of association types.

Figure 3.10 demonstrates the distribution of the three types across the ten pairs. Consistent with our aggregate results, the majority of subjects fall into the “Perform better under Preferred” type, representing approximately 50% of subjects in each pair.

Table 3.4: Definition of Association Type

| Association Type | Reports $X$ and $Y$: $AAD$ and $WTP$ |
|---|---|
| Perform Better under Preferred | $AAD_{Y(X)} < AAD_{X(Y)}$ and $WTP_{Y(X)} > WTP_{X(Y)}$ |
| Prefer Less but Better with More | $AAD_Y < AAD_X$ and $WTP_Y < WTP_X$ |
| Prefer More but Better with Less | $AAD_Y > AAD_X$ and $WTP_Y > WTP_X$ |

*Note:* The ten pairwise comparisons calibrate the association between preference and performance across the five reports. For each pair of reports, denoted as Report $X$ and Report $Y$, we refer to Report $X$ as the one with fewer features (regardless of informativeness), or less informative features, while Report $Y$ is the one with more features (regardless of informativeness), or more informative features. The notations, $Y(X)$ and $X(Y)$, mean that the same relationship holds when replacing all the $Y$ with $X$ and all the $X$ with $Y$.

This indicates that a significant portion of subjects demonstrate consistency between their preferences and performances.

Furthermore, there is notable heterogeneity among the inconsistent types, where subjects' preference and performance do not align. The second largest type is the "Prefer More but Better with Less" type, which comprises, on average, 22% of subjects. These individuals express a preference for the report with more or more informative features but actually perform better under the one with fewer or less informative features. Additionally, 13% of the subjects belong to the "Prefer Less but Better with More" type, indicating that they prefer the report with fewer or less informative features but achieve better performance under the one with more or more informative features. This diversity in the inconsistent types highlights the complex interplay between preferences and performances among the subjects.

To summarize,

**Result 6.** *On average, subjects are self-consistent between their preferences and performances, performing better under the sample feature they prefer. However, there is also non-negligible heterogeneity in the inconsistent association of ordinal rankings between preference and performance:*

- *Substantial inconsistencies are observed among subjects;*

- *The most prominent type of inconsistency is "Prefer More but Better with Less": subjects prefer the report that contains more features or more informative ones but actually perform better under the report that contains only the necessary features for their belief updating.*

Our results suggest that the non-standard use of sample features in belief updating is more likely to be intentional deviations rather than inattentive heuristics. In other words, subjects underestimate the usefulness of certain sample features, and fail to make optimal use of them when updating beliefs, despite these features being instrumentally more valuable for Bayesian inference compared to other features. For instance, our results shed light on biases such as the "Strength-Weight bias" or the "Sample-Size neglect" documented in previous literature (Kahneman and Tversky, 1972). These biases involve the evaluation of the sample proportion (referred to as "Strength") and sample size (referred to as "Weight"), respectively. Our findings indicate that these biases are primarily associated with subjects' over-valuing the importance of "Strength", while under-appreciating the importance of "Weight" when it comes to belief updating.

The majority type among subjects whose preferences are inconsistent with their performances is "Prefer More but Better with Less." This finding suggests that these subjects might fail to consider the cost-benefit trade-offs associated with processing additional sample features that do not matter for their belief updating. Despite the fact that the theoretically defined informativeness increases with more information, these subjects tend to prioritize quantity over relevance. In doing so, they may fail to recognize that the additional information does not necessarily improve the accuracy of their belief updating. Furthermore, this preference for more or more informative features may come at a cost. The additional effort or cognitive resources required to process these features can pose a challenge, potentially hindering subjects from making optimal use of the available information when updating their beliefs.

There is also a non-negligible fraction of subjects who demonstrate a lesser sophistication in understanding how additional sample features can aid in belief updating. This suggests that these individuals may not fully recognize the value of incorporating supplementary information for accurate belief revision. Furthermore, it is worth considering that non-standard preferences for information, such as a preference for simplicity, could potentially influence how they evaluate the usefulness of information.

## 3.5 Conclusion

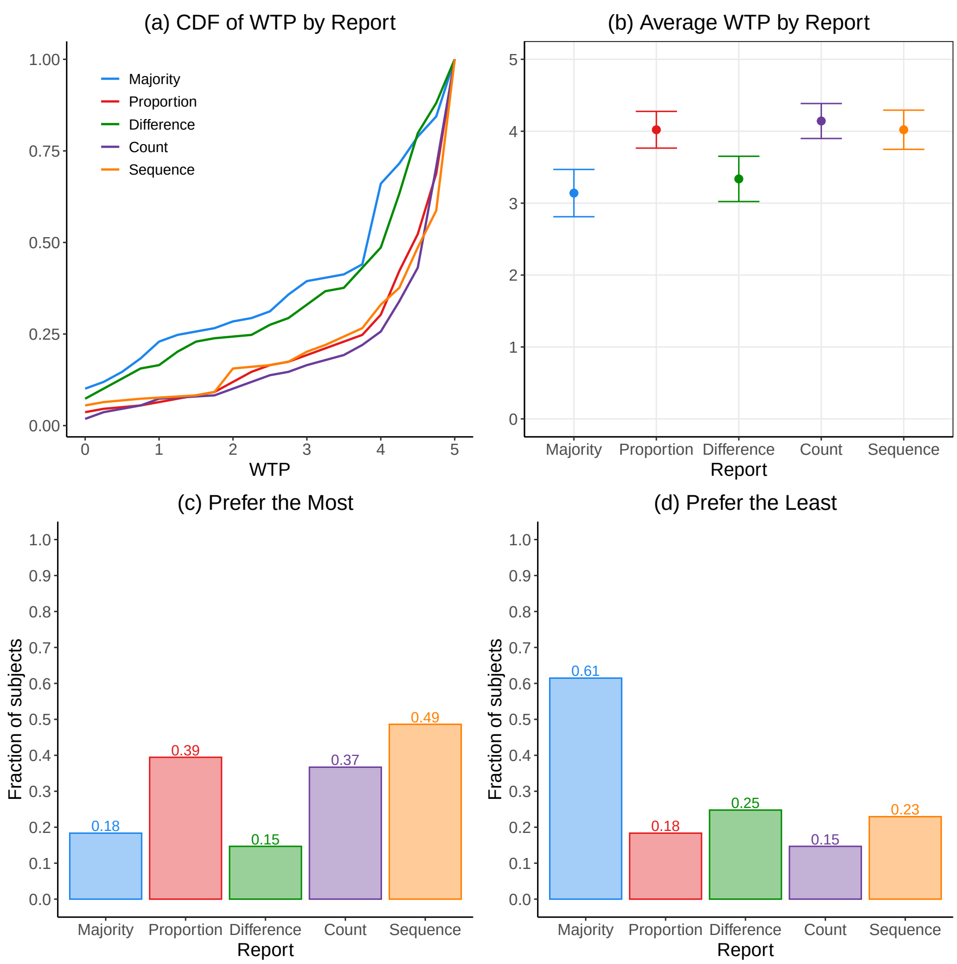
In this paper, we use a controlled laboratory experiment to study how individuals use and perceive the usefulness of different statistical characteristics of realized signals, namely sample features when updating beliefs. In terms of performance, a Bayesian agent would be equally good at processing each sample feature, as they use the Bayes' rule to do so. However, what we find is that subjects are not equally good at processing each sample feature. First of all, subjects under-use the information contained in each of the five sample features, while the magnitudes differ across sample features. We find that subjects are better at using *Proportion* than the other features: subjects' stated posteriors are closest to the Bayesian benchmark under *Proportion*, even though it is less informative compared to *Difference*, *Count*, and *Sequence*. Subjects deviate the most from the Bayesian benchmark under the least informative sample feature – *Majority*. These results provide direct evidence of "Strength-Weight Bias" – better at using sample proportion but worse at using sample size for belief updating.

In terms of preference, subjects' perceived usefulness of sample features also deviates from what instrumental value/informativeness would predict. Subjects value *Proportion* as equally useful as *Count* and *Sequence*, even though the latter two have higher instrumental value or more informative than the former one. Overall, subjects prefer the features that can back out *Proportion* with some computational operations over those that require additional inference or contingent reasoning on all the possible *Proportion* information. These results suggest that subjects have "Strength-Weight Preference" of the information – prefer using sample proportion rather than using sample size for belief updating.

Combining preference and performance, we show that, on average, subjects make better use of the sample features they prefer, while there exists notable heterogeneity in the inconsistency between preference and performance. This indicates that the biased use of sample features in belief updating is more likely to be an intentional deviation rather than inattentive heuristics. Overall, our results indicate that the suboptimal use of some informative sample features can account for a substantial amount of deviation from Bayesian benchmark in belief updating, which is positively correlated with how individuals perceive the usefulness of different sample features.

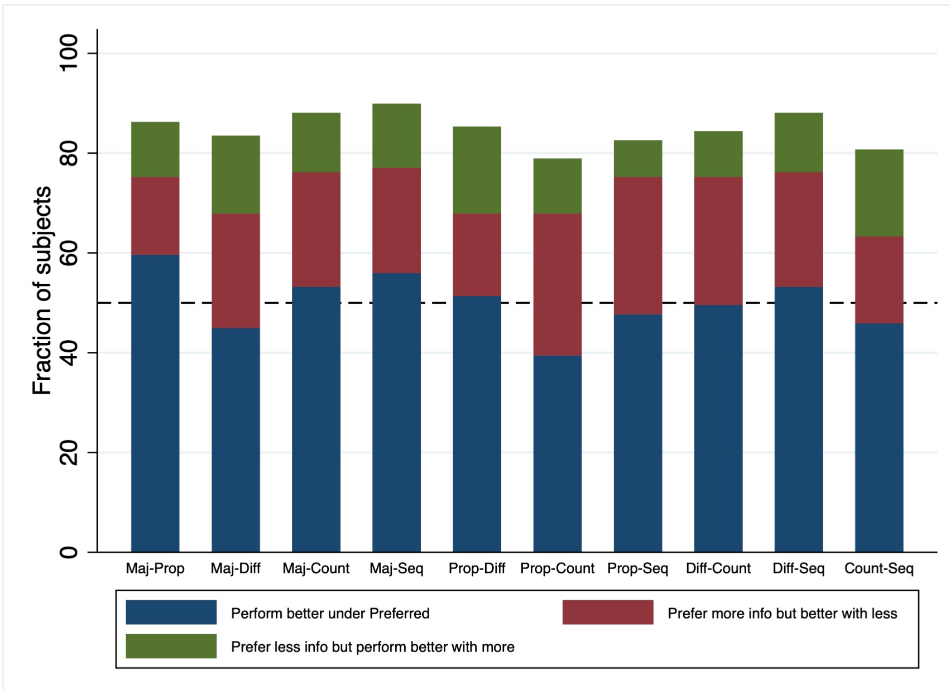
Our results open interesting questions for further research. One natural next step is to explore the generality of our current finding with other information on sample features. In our experiment, under less informative sample features, we deliberately choose the information that maps to different information under more informative ones. This allows us to see how the instrumental value of information would interact with the way subjects use the information in each sample feature. Thus, the information provided by different sample features maps to different Bayesian benchmarks, even if they have some sample features in common. For example, the Bayesian posterior under Report *Proportion* saying that 80% of balls are green is different from those under the Report *Count* either saying four green balls and one orange ball, 12 green balls and three orange balls, or 20 green balls and five orange balls, separately. As there is no one-to-one mapping between the information of sample features with different instrumental values, our results could be driven by the difference in Bayesian posteriors rather than the difference in subjective belief updating processes. Thus, it would be interesting for future work to explore to what extent our findings are due to the different updating behaviors.

Secondly, it would be interesting to directly ask whether subjects process the information to get certain sample features and use those to make inferences when receiving certain information and what behavioral traits drive their valuation of sample features. A contemporary paper by Bordalo et al. (2023) demonstrates that the similarity between information and hypothesis is one of the reasons behind this. However, as shown in Appendix G.1, our finding is not purely driven by reporting whatever they received. It would be a fruitful direction for future research.




*Note:* Panel (a) plots the cumulative density function of the reported willingness-to-pay, which is separated by reports. Panel (b) plots the average willingness-to-pay of each report. In Panel (b), 95% confidence intervals are included. Panel (c) plots the fraction of subjects who rank the report as the most preferred and separated by reports, and Panel (d) plots the fraction of subjects who rank the report as the least preferred (tied results are included).

Figure 3.9: Preference over Reports




*Note:* The fractions of subjects classified by the preference-performance types are plotted against the ten pairs of reports. In each pair, $X - Y$, the former name in short is Report $X$, the latter name in short is Report $Y$. $X$ either contains fewer features (regardless of informativeness) or less informative sample features than $Y$. In each pair of reports, a preference-performance association is defined as "Perform Better under Preferred" if a subject has a smaller average absolute deviation ($AAD$) and states a larger $WTP$ on one report than the alternative. A preference-performance association type is defined as "Prefer More but Better with Less" if a subject has a smaller $AAD$ but states a lower $WTP$ on Report $Y$ than Report $X$. A preference-performance relation is defined as "Prefer Less but Better with More" if a subject has a larger $AAD$ but states a larger $WTP$ on Report $Y$ than Report $X$. The dashed line represents 50% of subjects as the reference. Tied results are excluded.

Figure 3.10: Distribution of Association Types in 10 Report Pairs

# Appendices

## A. Proofs of the Propositions

### A.1 Proof of Proposition 1.3.1

Define the relative accuracy of the prior belief $\gamma \equiv \frac{\sigma_s^2}{\sigma_\theta^2}$, then $\mathbb{E}[\theta|s] = \frac{\gamma\mu_\theta + s}{1+\gamma}$ and $s^* = \overline{v} + \gamma(\overline{v} - \mu_\theta)$. Denote $z^* = \frac{s^* - \mu_\theta}{\sqrt{\sigma_s^2 + \sigma_\theta^2}}$. Also denote $\Phi(\cdot)$ and $\phi(\cdot)$ as the cumulative distribution function (cdf) and the probability density function (pdf) of standard normal distribution.

Given the setting, we can find the value of the information as follows:

$$
\begin{aligned}
&\mathbb{E}_s[v(s)] - v_0 \\
=&\overline{v}\Pr(s \leq s^*) + \mathbb{E}\left[\frac{\gamma\mu_\theta + s}{1+\gamma}\middle| s > s^*\right]\Pr(s > s^*) - v_0 \\
=&\overline{v} \cdot \Phi\left(\frac{s^* - \mu_\theta}{\sqrt{\sigma_s^2 + \sigma_\theta^2}}\right) + \left(\frac{\gamma\mu_\theta + \mathbb{E}[s|s > s^*]}{1+\gamma}\right)\left(1 - \Phi\left(\frac{s^* - \mu_\theta}{\sqrt{\sigma_s^2 + \sigma_\theta^2}}\right)\right) - v_0 \\
=&-\overline{v}(1 - \Phi(z^*)) + \left(\frac{\gamma\mu_\theta + \mu_\theta + \sqrt{\sigma_s^2 + \sigma_\theta^2}\phi(z^*)/(1 - \Phi(z^*))}{1+\gamma}\right)(1 - \Phi(z^*)) - (v_0 - \overline{v}) \\
=&(\mu_\theta - \overline{v})(1 - \Phi(z^*)) + \frac{\sqrt{\sigma_s^2 + \sigma_\theta^2}\phi(z^*)}{1+\gamma} - (v_0 - \overline{v}). \qquad (1)
\end{aligned}
$$

When $\mu_\theta \geq \overline{v}$, $v_0 = \mu_\theta$, and (1) becomes

$$-(\mu_\theta - \overline{v})\Phi\left(z^*\right) + \frac{\sqrt{\sigma_s^2 + \sigma_\theta^2}\phi(z^*)}{1+\gamma},$$

which decreases in $\mu_\theta - \overline{v}$. When $\mu_\theta < \overline{v}$, $v_0 = \overline{v}$, and (1) becomes

$$(\mu_\theta - \overline{v})(1 - \Phi\left(z^*\right)) + \frac{\sqrt{\sigma_s^2 + \sigma_\theta^2}\phi(z^*)}{1+\gamma},$$

which increases in $\mu_\theta - \overline{v}$.

We then show (1) increases in $\sigma_\theta^2$. Note that

$$\frac{\mathrm{d}\gamma}{\mathrm{d}\left(\sigma_\theta^2\right)} = -\frac{\sigma_s^2}{(\sigma_\gamma^2)^2} = -\frac{\gamma}{\sigma_\theta^2}$$

and

$$\frac{\mathrm{d}z^*}{\mathrm{d}\left(\sigma_\theta^2\right)} = \frac{-\frac{\gamma}{\sigma_\theta^2}(\overline{v} - \mu_\theta)\sqrt{\sigma_s^2 + \sigma_\theta^2} - \frac{(1+\gamma)(\overline{v}-\mu_\theta)}{2\sqrt{\sigma_s^2+\sigma_\theta^2}}}{\sigma_s^2 + \sigma_\theta^2} = \frac{-\frac{\gamma}{\sigma_\theta^2}(\overline{v} - \mu_\theta)\sqrt{\sigma_s^2 + \sigma_\theta^2} - \frac{z^*}{2}}{\sigma_\theta^2(1+\gamma)}.$$

Then

$$\begin{aligned}
&\frac{\mathrm{d}}{\mathrm{d}\left(\sigma_\theta^2\right)}\left\{(\mu_\theta - \overline{v})(1 - \Phi\left(z^*\right)) + \frac{\sqrt{\sigma_s^2 + \sigma_\theta^2}\phi(z^*)}{1+\gamma} - (v_0 - \overline{v})\right\} \\
=& -(\mu_\theta - \overline{v})\phi\left(z^*\right)\frac{\mathrm{d}z^*}{\mathrm{d}\sigma_\theta^2} + \frac{\frac{1+\gamma}{2\sqrt{\sigma_s^2+\sigma_\theta^2}} - \frac{-\gamma\sqrt{\sigma_s^2+\sigma_\theta^2}}{\sigma_\theta^2}}{(1+\gamma)^2}\phi(z^*) + \frac{\sqrt{\sigma_s^2 + \sigma_\theta^2}}{1+\gamma}\cdot(-z^*)\phi(z^*)\frac{\mathrm{d}z^*}{\mathrm{d}\sigma_\theta^2} \\
=& (\overline{v} - \mu_\theta)\phi\left(z^*\right)\frac{\mathrm{d}z^*}{\mathrm{d}\sigma_\theta^2} + \frac{\frac{\sigma_\theta^2(1+\gamma)}{2\sqrt{\sigma_s^2+\sigma_\theta^2}} + \gamma\sqrt{\sigma_s^2 + \sigma_\theta^2}}{\sigma_\theta^2(1+\gamma)^2}\phi(z^*) - (\overline{v} - \mu_\theta)\phi(z^*)\frac{\mathrm{d}z^*}{\mathrm{d}\sigma_\theta^2} \\
=& \frac{\sigma_\theta^2(1+\gamma) + 2\gamma(\sigma_s^2 + \sigma_\theta^2)}{2\sqrt{\sigma_s^2 + \sigma_\theta^2}\sigma_\theta^2(1+\gamma)^2}\phi(z^*) \\
=& \frac{\sigma_\theta^2(1+\gamma) + 2\gamma\sigma_\theta^2(1+\gamma)}{2\sqrt{\sigma_s^2 + \sigma_\theta^2}\sigma_\theta^2(1+\gamma)^2}\phi(z^*) = \frac{1+2\gamma}{2\sqrt{\sigma_s^2 + \sigma_\theta^2}(1+\gamma)}\phi(z^*) > 0.
\end{aligned}$$

Lastly, we show (1) decreases in $\sigma_s^2$.

$$\frac{\mathrm{d}\gamma}{\mathrm{d}\left(\sigma_s^2\right)} = \frac{1}{\sigma_\gamma^2}$$

and

$$\frac{\mathrm{d}z^*}{\mathrm{d}\left(\sigma_s^2\right)} = \frac{\frac{1}{\sigma_\theta^2}(\overline{v}-\mu_\theta)\sqrt{\sigma_s^2+\sigma_\theta^2} - \frac{(1+\gamma)(\overline{v}-\mu_\theta)}{2\sqrt{\sigma_s^2+\sigma_\theta^2}}}{\sigma_s^2+\sigma_\theta^2} = \frac{\frac{1}{\sigma_\theta^2}(\overline{v}-\mu_\theta)\sqrt{\sigma_s^2+\sigma_\theta^2} - \frac{z^*}{2}}{\sigma_\theta^2(1+\gamma)}.$$

Then

$$\begin{aligned}
&\frac{\mathrm{d}}{\mathrm{d}\left(\sigma_s^2\right)}\left\{(\mu_\theta-\overline{v})(1-\Phi\left(z^*\right)) + \frac{\sqrt{\sigma_s^2+\sigma_\theta^2}\phi(z^*)}{1+\gamma} - (v_0-\overline{v})\right\} \\
=&-(\mu_\theta-\overline{v})\phi\left(z^*\right)\frac{\mathrm{d}z^*}{\mathrm{d}\sigma_s^2} + \frac{\frac{1+\gamma}{2\sqrt{\sigma_s^2+\sigma_\theta^2}} - \frac{\sqrt{\sigma_s^2+\sigma_\theta^2}}{\sigma_\theta^2}}{(1+\gamma)^2}\phi(z^*) + \frac{\sqrt{\sigma_s^2+\sigma_\theta^2}}{1+\gamma}\cdot(-z^*)\phi(z^*)\frac{\mathrm{d}z^*}{\mathrm{d}\sigma_s^2} \\
=&(\overline{v}-\mu_\theta)\phi\left(z^*\right)\frac{\mathrm{d}z^*}{\mathrm{d}\sigma_\theta^2} + \frac{\frac{\sigma_\theta^2(1+\gamma)}{2\sqrt{\sigma_s^2+\sigma_\theta^2}} - \sqrt{\sigma_s^2+\sigma_\theta^2}}{\sigma_\theta^2(1+\gamma)^2}\phi(z^*) - (\overline{v}-\mu_\theta)\phi(z^*)\frac{\mathrm{d}z^*}{\mathrm{d}\sigma_\theta^2} \\
=&\frac{\sigma_\theta^2(1+\gamma) - 2(\sigma_s^2+\sigma_\theta^2)}{2\sqrt{\sigma_s^2+\sigma_\theta^2}\sigma_\theta^2(1+\gamma)^2}\phi(z^*) \\
=&\frac{\sigma_\theta^2(1+\gamma) - 2\gamma\sigma_\theta^2(1+\gamma)}{2\sqrt{\sigma_s^2+\sigma_\theta^2}\sigma_\theta^2(1+\gamma)^2}\phi(z^*) = \frac{-1}{2\sqrt{\sigma_s^2+\sigma_\theta^2}(1+\gamma)}\phi(z^*) < 0.
\end{aligned}$$

Thus (1) decreases in $\gamma\left(\equiv \frac{\sigma_s^2}{\sigma_\theta^2}\right)$.

## A.2 Proof of Incentive Compatibility of the Ranking-Card

Let $X_f = \{f_1,\ldots,f_N\}$ be the set of forms and $X_m = \{m_1,\ldots,m_K\}$ be the set of bundles "null information for + compensation". Let $X = X_f \bigcup X_m$ be the choice set.

**Assumption 6.** *$X$ is well-ordered under $\succsim$.*

Since $X$ is a finite set, there is a utility function $u : X \to \mathbb{R}$ represents $\succsim$.

Let $R : X \to \mathbb{Z}$ be the *ranking* function that the agent assigns. Particularly, the agent sort the elements in $X$. We define $R(x)$ the number of elements *behind* $x$. For example, suppose an agent sort $X = \{a, b, c, d\}$ in the following order:

$$a, d, e \sim b, c$$

Note that $e$ and $b$ are at the same place. Then $R(a) = 4$, $R(d) = 3$, $R(e) = R(b) = 1$ and $R(c) = 0$.

In each trial, two elements in $X$ will be chosen, and the one with higher ranking will be selected. Denote $C(\{x, y\})$ as the selected element given $x, y \in X$, then

$$C(\{x, y\}) = \begin{cases} \arg\max_{z \in \{x,y\}} R(z) & \text{if } R(x) \neq R(y) \\ x & \text{if } R(x) = R(y). \end{cases}$$

The selected element derives the agent's realized utility, $u(C(\{x, y\})$.

We then give the main characterization of the utility function given the binary choice.

**Proposition.** For any $x, y \in X$, $u(x) \geq u(y)$ if and only if $R(x) \geq R(y)$.

*Proof.* The necessity part is trivial. We show the sufficiency part here. Assume $u(x) < u(y)$. Suppose $R(x) \geq R(y)$. Consider the case that $x$ and $y$ are both chosen. Then $C(\{x, y\}) = x$, and the implied utility specification is $u(x)$, which is strictly less than $u(y)$ and hence leads to a contradiction. ∎

Since the ranking function characterizes the utility function, there is no incentive to state the preferences otherwise. Therefore, the ranking must be truthful.

# B. Experiment Details of Chapter 1

Table B1: Summary Statistics

| | FC | T3 | RA | T3* | RA* | Total |
|---|---|---|---|---|---|---|
| # of Subjects | 207.00 | 217.00 | 208.00 | 233.00 | 201.00 | 213.78 |
| Female (%) | 61.84 | 64.06 | 66.83 | 61.37 | 61.19 | 63.04 |
| Age | 29.59 | 28.58 | 29.67 | 28.57 | 28.65 | 29.00 |
| Household Yearly Income $\geq$ 40k (%) | 10.63 | 8.29 | 8.65 | 11.16 | 9.45 | 9.66 |
| Received At Least 1 Vaccine (%) | 91.30 | 93.55 | 90.38 | 94.42 | 89.55 | 91.93 |

*Notes.* FC represents the treatment Free Choice, T3 the Top 3 Choices, and RA the Random Assignment. The treatments with asteroids represents the treatments with no unused information preference questions.

Table B2: Vaccine Performance Information

| Vaccine | Platform | Development Countries | Recommended Doses | Current Phase |
|---|---|---|---|---|
| AstraZeneca | virus vector | UK/Sweden | 2; Day 0 + 28 | 4 |
| Johnson & Johnson | virus vector | Netherland/Belgium/US | 1 | 4 |
| Moderna | mRNA | US | 2; Day 0 + 28 | 4 |
| Pfizer | mRNA | US/Germany | 2; Day 0 + 21 | 4 |
| Sinovac | inactive virus | China | 2; Day 0 + 14 | 4 |

| Vaccine | Efficacy | Hospitalization Prevention Rate | Adverse Event Rates | Severe Adverse Event Rates |
|---|---|---|---|---|
| AstraZeneca | 70.4% | 100% | Vaccinated: 27.03%<br>Placebo: 16.33% | Vaccinated: 0.7%<br>Placebo: 0.8% |
| Johnson & Johnson | 66.9% | 93.1% | Vaccinated: 68.1%<br>Placebo: 29.4% | Vaccinated: 0.1%<br>Placebo: 0.1% |
| Moderna | 94.1% | 100% | Vaccinated: 79.4%<br>Placebo: 36.5% | Vaccinated: 1.5%<br>Placebo: 1.3% |
| Pfizer | 95.0% | 88.9% | Vaccinated: 26.7%<br>Placebo: 12.2% | Vaccinated: 1.1%<br>Placebo: 0.6% |
| Sinovac | 83.5% | 100% | Vaccinated: 18.9%<br>Placebo: 16.9% | Vaccinated: 0.3%<br>Placebo: 0.2% |

*Note:* See Voysey et al. (2021), Sadoff et al. (2021), Baden et al. (2021), Polack et al. (2020), Tanriover et al. (2021).

Table B3: Interaction Data With the Vaccine Information

| | Top-Ranked | Requested | All |
|---|---|---|---|
| *Bottom Clicked (%)* | | | |
| Vaccine Platform | 83.4 | 82.5 | 79.7 |
| Countries | 82.3 | 82.2 | 79.3 |
| Doses | 82.3 | 82.1 | 79.1 |
| Research Phase | 82.7 | 82.3 | 79.1 |
| Efficacy | 82.7 | 82.9 | 80.0 |
| Hospital | 82.1 | 81.9 | 79.1 |
| Adverse Event | 82.3 | 81.9 | 78.7 |
| Severe AE | 80.7 | 79.8 | 76.7 |
| *Time on page (sec)* | | | |
| Mean | 52.90 | 50.00 | 47.06 |
| Median | 45.44 | 39.55 | 37.44 |
| $N$ | 481 | 1,150 | 1,762 |

*Notes.* The table includes all subjects from the three main treatment groups. The first column contains observations of the highest-ranked information (according to **Ranking** question). The second column contains observations of the requested information.

# C. Appendix Tables for Chapter 1

Table C1: Summary by Vaccine

| | Efficacy | | | | |
|---|---|---|---|---|---|
| | Pfizer | Moderna | AstraZeneca | J&J | Sinovac |
| Pre-treatment Beliefs | 78.03 | 79.72 | 72.51 | 66.27 | 48.49 |
| | (16.18) | (15.15) | (15.09) | (19.16) | (23.51) |
| Post-treatment Beliefs | 82.69 | 83.72 | 76.95 | 68.46 | 48.70 |
| | (15.27) | (14.90) | (16.01) | (21.02) | (26.87) |
| Adjustment in Beliefs (Post − Pre) | 4.652 | 4.003 | 4.435 | 2.193 | 0.217 |
| | (13.81) | (13.40) | (14.30) | (18.26) | (21.52) |
| $\frac{\lvert\text{Adjustment in Beliefs}\rvert}{textPre-treatmentBeliefs}$ | 9.896 | 9.566 | 10.47 | 12.44 | 14.68 |
| | (10.70) | (10.19) | (10.69) | (13.53) | (15.72) |
| diff_abs_ratio | 0.186 | 0.209 | 0.220 | 0.326 | 0.527 |
| | (0.622) | (1.442) | (0.930) | (1.057) | (1.560) |
| \| Pre-treatment Error \| | 17.19 | 14.59 | 11.29 | 14.29 | 35.71 |
| | (15.94) | (14.95) | (10.22) | (12.77) | (22.44) |
| \| Post-treatment Error \| | 13.01 | 11.43 | 13.34 | 15.83 | 35.97 |
| | (14.68) | (14.11) | (11.00) | (13.91) | (25.27) |
| Learning | 4.177 | 3.157 | -2.052 | -1.538 | -0.263 |
| | (13.36) | (12.82) | (11.32) | (14.27) | (19.95) |

| | Hospital Prevention Rate | | | | |
|---|---|---|---|---|---|
| | Pfizer | Moderna | AstraZeneca | J&J | Sinovac |
| Pre-treatment Beliefs | 78.06 | 79.00 | 75.33 | 69.86 | 52.76 |
| | (20.50) | (20.01) | (19.98) | (22.47) | (26.51) |
| Post-treatment Beliefs | 84.02 | 85.53 | 82.47 | 73.34 | 53.56 |
| | (17.82) | (18.20) | (19.64) | (23.19) | (30.24) |
| Adjustment in Beliefs (Post − Pre) | 5.962 | 6.530 | 7.133 | 3.476 | 0.801 |
| | (20.47) | (20.83) | (20.27) | (22.40) | (24.05) |
| $\frac{\lvert\text{Adjustment in Beliefs}\rvert}{textPre-treatmentBeliefs}$ | 13.25 | 13.56 | 14.39 | 15.31 | 16.63 |
| | (16.70) | (17.10) | (15.96) | (16.71) | (17.38) |
| diff_abs_ratio | 0.498 | 0.429 | 0.358 | 0.426 | 0.708 |
| | (3.540) | (2.429) | (1.404) | (1.263) | (3.476) |
| \| Pre-treatment Error \| | 14.33 | 21.00 | 24.67 | 23.99 | 47.24 |
| | (18.23) | (20.01) | (19.98) | (21.66) | (26.51) |
| \| Post-treatment Error \| | 11.59 | 14.47 | 17.53 | 21.14 | 46.44 |
| | (14.38) | (18.20) | (19.64) | (21.94) | (30.24) |
| Learning | 2.738 | 6.530 | 7.133 | 2.853 | 0.801 |
| | (18.89) | (20.83) | (20.27) | (21.30) | (24.05) |

| | Adverse Event Rate | | | | |
|---|---|---|---|---|---|
| | Pfizer | Moderna | AstraZeneca | J&J | Sinovac |
| Pre-treatment Beliefs | 58.50 | 62.94 | 72.73 | 56.52 | 53.13 |
| | (27.73) | (26.33) | (24.26) | (25.91) | (27.74) |
| Post-treatment Beliefs | 51.85 | 54.96 | 59.84 | 50.20 | 46.16 |
| | (29.52) | (29.48) | (28.76) | (27.15) | (29.80) |
| Adjustment in Beliefs (Post − Pre) | -6.649 | -7.981 | -12.89 | -6.320 | -6.972 |
| | (29.75) | (28.78) | (28.27) | (28.19) | (29.58) |
| $\frac{\lvert\text{Adjustment in Beliefs}\rvert}{textPre-treatmentBeliefs}$ | 21.46 | 21.05 | 21.44 | 21.00 | 21.73 |
| | (21.64) | (21.18) | (22.47) | (19.82) | (21.22) |
| diff_abs_ratio | 0.656 | 0.587 | 0.528 | 0.601 | 0.652 |
| | (1.616) | (1.641) | (1.872) | (1.185) | (1.394) |
| \| Pre-treatment Error \| | 36.03 | 23.51 | 42.28 | 22.02 | 37.49 |
| | (21.95) | (20.27) | (18.63) | (17.88) | (23.14) |
| \| Post-treatment Error \| | 32.13 | 29.41 | 33.36 | 25.95 | 32.25 |
| | (21.69) | (24.53) | (20.32) | (19.58) | (24.29) |
| Learning | 3.891 | -5.893 | 8.922 | -3.932 | 5.234 |
| | (22.54) | (24.84) | (19.96) | (21.60) | (24.59) |

| | Severe Adverse Event Rate | | | | |
|---|---|---|---|---|---|
| | Pfizer | Moderna | AstraZeneca | J&J | Sinovac |
| Pre-treatment Beliefs | 30.36 | 32.10 | 38.20 | 30.44 | 32.71 |
| | (28.17) | (29.43) | (31.52) | (27.52) | (29.24) |
| Post-treatment Beliefs | 27.28 | 28.58 | 32.23 | 27.16 | 30.56 |
| | (29.89) | (30.69) | (32.38) | (28.44) | (30.27) |
| Adjustment in Beliefs (Post − Pre) | -3.084 | -3.521 | -5.967 | -3.280 | -2.152 |
| | (24.71) | (24.09) | (24.94) | (23.17) | (23.87) |
| $\frac{\lvert\text{Adjustment in Beliefs}\rvert}{textPre-treatmentBeliefs}$ | 15.44 | 15.14 | 16.50 | 14.86 | 15.33 |
| | (19.53) | (19.06) | (19.62) | (18.07) | (18.41) |
| diff_abs_ratio | 0.942 | 0.990 | 0.834 | 1.021 | 1.048 |
| | (2.905) | (4.686) | (3.847) | (4.773) | (3.840) |
| \| Pre-treatment Error \| | 29.32 | 30.71 | 37.52 | 30.35 | 32.44 |
| | (28.11) | (29.31) | (31.50) | (27.51) | (29.21) |
| \| Post-treatment Error \| | 26.28 | 27.28 | 31.58 | 27.07 | 30.30 |
| | (29.80) | (30.51) | (32.33) | (28.43) | (30.23) |
| Learning | 3.050 | 3.434 | 5.942 | 3.278 | 2.145 |
| | (24.69) | (24.00) | (24.91) | (23.16) | (23.84) |

Table C2: Reported Ranking on Each Vaccine

| Rank | AstraZeneca | J & J | Moderna | Pfizer | Sinovac |
|---|---|---|---|---|---|
| 1st | 212 | 50 | 240 | 342 | 26 |
| | (24.37%) | (5.75%) | (27.59%) | (39.31%) | (2.99%) |
| 2nd | 174 | 55 | 368 | 249 | 24 |
| | (20.00%) | (6.32%) | (42.30%) | (28.62%) | (2.76%) |
| 3rd | 335 | 138 | 159 | 185 | 53 |
| | (38.51%) | (15.86%) | (18.28%) | (21.26%) | (6.09%) |
| 4th | 110 | 528 | 73 | 58 | 101 |
| | (12.64%) | (60.69%) | (8.39%) | (6.67%) | (11.61%) |
| 5th | 39 | 99 | 30 | 36 | 666 |
| | (4.48%) | (11.38%) | (3.45%) | (4.14%) | (76.55%) |

Table C3: The Number of Information Sheets Requested

| Treatments | Full Compliance | Top 3 | Assigned | Total |
|---|---|---|---|---|
| None | 21 | 28 | 29 | 78 |
| | (10%) | (13%) | (14%) | (12%) |
| Top 1 | 22 | 23 | 22 | 67 |
| | (10%) | (11%) | (10%) | (11%) |
| Top 2 | 31 | 35 | 39 | 105 |
| | (15%) | (16%) | (19%) | (17%) |
| Top 3 | 136 | 132 | 118 | 286 |
| | (65%) | (61%) | (57%) | (61%) |

Table C4: Vaccine Background Knowledge and Receptions

| | Pfizer | Moderna | AstraZeneca | J & J | Sinovac | Medigen |
|---|---|---|---|---|---|---|
| Correct Recommended Doses (%) | 81.33 | 87.90 | 87.71 | 41.18 | 33.30 | 74.77 |
| | (38.98) | (32.63) | (32.85) | (49.24) | (47.15) | (43.46) |
| Correct Platform (%) | 62.48 | 64.07 | 39.59 | 18.11 | 23.92 | 49.44 |
| | (48.44) | (48.00) | (48.93) | (38.52) | (42.68) | (50.02) |
| Familiarity (1-7) | 4.624 | 4.662 | 4.933 | 3.127 | 2.712 | 4.216 |
| | (1.239) | (1.216) | (1.208) | (1.325) | (1.395) | (1.484) |
| Registered (%) | 47.94 | 49.25 | 67.45 | 3.752 | 1.876 | 12.85 |
| | (49.98) | (50.02) | (46.88) | (19.01) | (13.57) | (33.48) |
| Received (%) | 27.39 | 9.287 | 52.35 | 0.657 | 0.563 | 7.129 |
| | (44.62) | (29.04) | (49.97) | (8.081) | (7.485) | (25.74) |

*Notes.* Standard deviations are in the parentheses.

Table C5: Information Preference and Selection—Only Available Vaccines

| | *Dependent Variables* | | | |
|---|---|---|---|---|
| | Info Rank | | Selected | |
| | (1) | (2) | (3) | (4) |
| | Belief Ranking | Gap from Highest | Belief Ranking | Gap from Highest |
| Efficacy | 0.12$^{***}$ | -0.01$^{**}$ | 2.83$^{**}$ | -0.34$^{*}$ |
| | (0.03) | (0.00) | (0.97) | (0.15) |
| Hospitalization Prevention | 0.08$^{**}$ | -0.01$^{**}$ | 2.88$^{**}$ | -0.30 |
| | (0.03) | (0.00) | (1.11) | (0.18) |
| Adverse Events | -0.03 | -0.00 | 0.70 | 0.08 |
| | (0.02) | (0.00) | (0.85) | (0.06) |
| Severe Adverse Events | -0.03 | -0.00 | -1.17 | -0.15 |
| | (0.02) | (0.00) | (0.85) | (0.10) |
| Familiarity | 0.04$^{*}$ | 0.05$^{**}$ | 3.43$^{**}$ | 3.60$^{***}$ |
| | (0.02) | (0.02) | (1.05) | (1.06) |
| Constants | 2.89$^{***}$ | 3.65$^{***}$ | 19.20$^{*}$ | 43.85$^{***}$ |
| | (0.18) | (0.11) | (9.25) | (7.55) |
| Observations | 1891 | 1891 | 1891 | 1891 |
| Subjects | 632 | 632 | 632 | 632 |
| $R^2$ | 0.046 | 0.038 | 0.039 | 0.038 |
| Mean of Dep. Variable | 3.73 | 3.73 | 66.5 | 66.5 |

*Notes.* Clustered (on subject level) standard errors in parentheses. The subjects' family income, college majors, and sex are controlled. The coefficients and the mean of the dependent variable in (3) and (4) are in percentage. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ .

Table C6: Information Preference and Selection—With Vaccine Reception History

| | *Dependent Variables* | | | |
|---|---|---|---|---|
| | Info Rank | | Selected | |
| | (1) | (2) | (3) | (4) |
| | Belief Ranking | Gap from Highest | Belief Ranking | Gap from Highest |
| Efficacy | 0.14** | -0.01 | 2.57 | -0.24 |
| | (0.05) | (0.01) | (1.72) | (0.24) |
| Hospitalization Prevention | 0.14** | -0.03*** | 3.39* | -0.55* |
| | (0.05) | (0.01) | (1.71) | (0.28) |
| Adverse Events | -0.05 | 0.00 | 1.27 | 0.09 |
| | (0.03) | (0.00) | (1.49) | (0.09) |
| Severe Adverse Events | -0.05 | -0.00 | -0.86 | 0.03 |
| | (0.04) | (0.00) | (1.43) | (0.13) |
| Familiarity | 0.12** | 0.12** | 4.83** | 4.91** |
| | (0.04) | (0.04) | (1.62) | (1.63) |
| Constants | 2.56*** | 3.56*** | 10.62 | 37.52** |
| | (0.40) | (0.30) | (15.26) | (11.46) |
| Observations | 572 | 572 | 572 | 572 |
| Subjects | 532 | 532 | 532 | 532 |
| Mean of Dep. Variable | 3.88 | 3.88 | 69.2 | 69.2 |

*Notes.* Clustered (at subject level) standard errors in parentheses. The subjects' family income, college majors, and sex are controlled. The coefficients and the mean of the dependent variable in (3) and (4) are in percentage. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ .

Table C7: Update in Beliefs—Adding Vaccine Reception History

| | *Belief Update*: Post-Treatment Belief − Pre-Treatment Belief | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Efficacy | | | Hospitalization | | |
| Signal Disagreement | 0.31*** | 0.28*** | 0.28*** | 0.52*** | 0.63*** | 0.64*** |
| | (0.03) | (0.04) | (0.04) | (0.04) | (0.05) | (0.05) |
| Familiarity | 0.45 | | 0.13 | 1.43** | | 0.86 |
| | (0.31) | | (0.33) | (0.48) | | (0.47) |
| Selected Top 3 | | 2.82* | 2.74* | | 4.40** | 3.80** |
| | | (1.15) | (1.12) | | (1.42) | (1.41) |
| Not Selected Top 3 | | 0.06 | 0.21 | | 0.75 | 0.54 |
| | | (1.43) | (1.44) | | (1.73) | (1.74) |
| Received the Vaccine Before | 1.86* | 1.95** | 1.85* | 1.77 | 1.89* | 1.20 |
| | (0.74) | (0.66) | (0.73) | (0.92) | (0.77) | (0.89) |
| Constants | -1.69 | -1.55 | -2.14 | -14.39*** | -10.91** | -13.95*** |
| | (2.28) | (2.13) | (2.59) | (3.90) | (3.44) | (3.92) |
| Observations | 1754 | 1762 | 1754 | 1754 | 1762 | 1754 |
| Subjects | 611 | 611 | 611 | 611 | 611 | 611 |
| $R^2$ | 0.16 | 0.20 | 0.20 | 0.29 | 0.34 | 0.34 |
| Mean of Dep. Variable | 4.29 | 4.26 | 4.29 | 6.64 | 6.65 | 6.64 |
| Pre-treatment Beliefs Controlled? | No | Yes | Yes | No | Yes | Yes |

*Notes.* Clustered (at subject level) standard errors in parentheses. The subjects' family income, college majors, and sex are controlled in all models. Pre-Treatment beliefs are controlled in models (2), (3), (5), and (6). Only the observations that subjects have received that vaccine before are included. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ .

Table C8: Update in Beliefs—Only Underestimate (Information $\geq$ Belief)

| | *Belief Update*: Post-Treatment Belief − Pre-Treatment Belief | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Efficacy | | | Hospitalization | | |
| Signal Strength | 0.34$^{***}$ | 0.31$^{***}$ | 0.31$^{***}$ | 0.53$^{***}$ | 0.66$^{***}$ | 0.67$^{***}$ |
| | (0.05) | (0.06) | (0.06) | (0.04) | (0.05) | (0.05) |
| Familiarity | 0.56 | | 0.10 | 1.51$^{**}$ | | 0.84 |
| | (0.41) | | (0.42) | (0.52) | | (0.52) |
| Selected Top 3 | | 3.47$^{*}$ | 3.38$^{*}$ | | 5.07$^{***}$ | 4.44$^{**}$ |
| | | (1.44) | (1.40) | | (1.53) | (1.52) |
| Not Selected Top 3 | | 0.41 | 0.57 | | 0.97 | 0.73 |
| | | (1.77) | (1.79) | | (1.87) | (1.89) |
| Constants | -2.82 | -2.42 | -2.97 | -15.84$^{***}$ | -12.82$^{***}$ | -15.73$^{***}$ |
| | (2.94) | (2.57) | (3.18) | (4.30) | (3.78) | (4.30) |
| Observations | 1273 | 1278 | 1273 | 1531 | 1539 | 1531 |
| Subjects | 598 | 598 | 598 | 605 | 605 | 605 |
| $R^2$ | 0.14 | 0.19 | 0.19 | 0.28 | 0.34 | 0.34 |
| Mean of Dep. Variable | 6.24 | 6.22 | 6.24 | 8.07 | 8.07 | 8.07 |
| Pre-treatment Beliefs Controlled? | No | Yes | Yes | No | Yes | Yes |

*Notes.* Clustered (at subject level) standard errors in parentheses. The subjects' family income, college majors, and sex are controlled in all models. Pre-Treatment beliefs are controlled in models (2), (3), (5), and (6). Only the observations with underestimated pre-treatment beliefs (relative to the information) are included. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ .

Table C9: Update in Beliefs—Only Overestimate (Information < Belief)

| | *Belief Update*: Post-Treatment Belief − Pre-Treatment Belief | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Efficacy | | | Hospitalization | | |
| Signal Strength | $0.33^{***}$ | $0.34^{***}$ | $0.34^{***}$ | $0.84^{***}$ | $0.79^{**}$ | $0.85^{***}$ |
| | (0.08) | (0.08) | (0.08) | (0.23) | (0.24) | (0.25) |
| Familiarity | 0.62 | | 0.50 | 0.91 | | 0.88 |
| | (0.44) | | (0.45) | (0.74) | | (0.71) |
| Selected Top 3 | | 1.56 | 1.39 | | -1.44 | -1.68 |
| | | (1.74) | (1.72) | | (2.31) | (2.27) |
| Not Selected Top 3 | | -0.13 | -0.04 | | 0.96 | 0.84 |
| | | (2.06) | (2.07) | | (2.52) | (2.42) |
| Constants | -1.69 | 0.17 | -1.72 | -3.92 | 1.12 | -2.28 |
| | (3.17) | (3.12) | (3.79) | (5.07) | (3.62) | (4.96) |
| Observations | 481 | 484 | 481 | 223 | 223 | 223 |
| Subjects | 395 | 397 | 395 | 203 | 203 | 203 |
| $R^2$ | 0.082 | 0.10 | 0.10 | 0.065 | 0.072 | 0.078 |
| Mean of Dep. Variable | -0.89 | -0.92 | -0.89 | -3.16 | -3.16 | -3.16 |
| Pre-treatment Beliefs Controlled? | No | Yes | Yes | No | Yes | Yes |

*Notes.* Clustered (at subject level) standard errors in parentheses. The subjects' family income, college majors, and sex are controlled in all models. Pre-Treatment beliefs are controlled in models (2), (3), (5), and (6). Only the observations with overestimated pre-treatment beliefs (relative to the information) are included. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ .

Table C10: Changes in Beliefs of Different Demands

| | \| Post-error \| | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Efficacy | Hospitalization | Efficacy | Hospitalization |
| \| Pre-error \| | 0.664*** | 0.578*** | 0.781*** | 0.807*** |
| | (0.0257) | (0.0323) | (0.0306) | (0.0324) |
| Selected Top 3 – Received | -8.086*** | -12.98*** | -3.756*** | 0.113 |
| | (0.641) | (0.959) | (0.995) | (1.137) |
| – Not Received | -6.595*** | -10.72*** | -1.638 | 2.710 |
| | (0.784) | (1.308) | (1.228) | (1.722) |
| Not Selected Top 3 – Received | -5.724*** | -9.249*** | -1.394 | 1.664 |
| | (1.117) | (1.671) | (1.484) | (2.107) |
| – Not Received | -3.736** | -7.652*** | 2.317 | 2.813 |
| | (1.156) | (1.662) | (1.421) | (2.528) |
| Not Top 3 – Received | -5.220*** | -7.452*** | -1.215 | -0.487 |
| | (0.971) | (1.401) | (1.290) | (1.990) |
| – Not Received | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) |
| \| Pre-error \| × Received Selected Top 3 | | | -0.216*** | -0.498*** |
| | | | (0.0654) | (0.0406) |
| \| Pre-error \| × Not Received Selected Top 3 | | | -0.258** | -0.464*** |
| | | | (0.0819) | (0.0715) |
| \| Pre-error \| × Received Non-selected Top 3 | | | -0.206* | -0.350*** |
| | | | (0.104) | (0.0992) |
| \| Pre-error \| × Not Received Non-selected Top 3 | | | -0.290*** | -0.313** |
| | | | (0.0768) | (0.102) |
| \| Pre-error \| × Received Non-Top 3 | | | -0.164** | -0.191** |
| | | | (0.0582) | (0.0584) |
| Constants | 8.952*** | 19.15*** | 6.184*** | 11.16*** |
| | (1.417) | (2.818) | (1.470) | (2.773) |
| Observations | 3160 | 3160 | 3160 | 3160 |
| Subjects | 632 | 632 | 632 | 632 |

Standard errors in parentheses. Family income, college majors, and sex are controlled.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# D. Appendix Tables for Chapter 2

Table D1: Baseline Results: Forced Voting Changes

| | *Vote Changes (Forced):* Post Vote − Pre Vote | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Nuclear Power | Algal Reef | Pork Import | Election |
| Eligible | -0.004 | -0.291$^{+}$ | -0.046 | 0.038 |
| | (0.127) | (0.151) | (0.090) | (0.092) |
| Positive Treatment | 0.012 | -0.211 | 0.213$^{*}$ | 0.356$^{***}$ |
| | (0.108) | (0.156) | (0.099) | (0.094) |
| Negative Treatment | -0.024 | -0.431$^{**}$ | -0.103 | 0.029 |
| | (0.143) | (0.163) | (0.099) | (0.092) |
| Eligible × Positive Treatment ($\gamma^{\text{Positive}}$) | 0.014 | 0.533$^{**}$ | -0.028 | -0.235$^{+}$ |
| | (0.175) | (0.190) | (0.131) | (0.131) |
| Eligible × Negative Treatment ($\gamma^{\text{Negative}}$) | -0.465$^{*}$ | 0.250 | -0.042 | 0.012 |
| | (0.206) | (0.210) | (0.138) | (0.126) |
| Constants | 0.262 | 0.220 | 0.061 | 0.048 |
| | (0.165) | (0.172) | (0.127) | (0.113) |
| Vote Change in Each Treatment Between Eligibility | | | | |
| $\delta + \gamma^{\text{Positive}}$ | 0.010 | 0.241$^{+}$ | -0.073 | -0.197$^{*}$ |
| | (0.123) | (0.124) | (0.095) | (0.092) |
| $\delta + \gamma^{\text{Negative}}$ | -0.469$^{**}$ | -0.042 | -0.088 | 0.050 |
| | (0.166) | (0.136) | (0.104) | (0.081) |
| Subjects | 185 | 207 | 392 | 392 |
| Mean of Dep. Var. | 0.119 | -0.058 | 0.059 | 0.110 |
| Pre-treatment Yea Share | 0.492 | 0.623 | 0.457 | 0.446 |
| Post-treatment Yea Share | 0.611 | 0.565 | 0.515 | 0.556 |

*Notes.* (i) Standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ (ii) *Vote Change in Each Treatment Between Eligibility* estimates (with Wald estimator) the difference in the vote changes in each treatment group between eligible and ineligible subjects. (iii) The education backgrounds (whether the subject studies at a public school, or studies social science), sex, household income, and their favorite political party are controlled.

Table D2: Baseline Results: Support Changes

| | *Support Changes* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Nuclear Power | Algal Reef | Pork Import | Election |
| Eligible | 0.53 | -0.10 | -0.51 | 0.03 |
| | (0.58) | (0.74) | (0.53) | (0.47) |
| Positive Treatment | -0.49 | -0.14 | 0.47 | $1.73^{***}$ |
| | (0.50) | (0.74) | (0.51) | (0.48) |
| Negative Treatment | -0.25 | $-1.63^{*}$ | $-1.66^{***}$ | -0.10 |
| | (0.84) | (0.72) | (0.47) | (0.48) |
| Eligible × Positive Treatment ($\gamma^{\text{Positive}}$) | 0.39 | 1.46 | 0.28 | -0.73 |
| | (0.82) | (0.97) | (0.73) | (0.63) |
| Eligible × Negative Treatment ($\gamma^{\text{Negative}}$) | $-3.31^{**}$ | 0.18 | 0.21 | 0.10 |
| | (1.11) | (0.98) | (0.83) | (0.64) |
| Constants | $1.82^{*}$ | -0.19 | 0.58 | 0.36 |
| | (0.85) | (0.89) | (0.69) | (0.54) |
| Support Change in Each Treatment Between Eligibility | | | | |
| $\delta + \gamma^{\text{Positive}}$ | 0.92 | $1.36^{*}$ | -0.22 | $-0.70^{+}$ |
| | (0.61) | (0.65) | (0.49) | (0.41) |
| $\delta + \gamma^{\text{Negative}}$ | $-2.78^{**}$ | 0.08 | -0.30 | 0.13 |
| | (1.01) | (0.65) | (0.63) | (0.43) |
| Subjects | 185 | 207 | 392 | 392 |
| Mean of Dep. Var. | 0.422 | -0.498 | 0.128 | 0.561 |
| Pre-treatment Support | 5.092 | 5.947 | 5.168 | 4.745 |
| Post-treatment Support | 5.514 | 5.449 | 5.296 | 5.306 |

*Notes.* (i) Standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ (ii) *Support Change in Each Treatment Between Eligibility* estimates (with Wald estimator) the difference in the support changes in each treatment group between eligible and ineligible subjects. (iii) The education backgrounds (whether the subject studies at a public school, or studies social science), sex, household income, and their favorite political party are controlled.

Table D3: Baseline Results: Standardized Support Changes

| | *Standardized Support Changes* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Nuclear Power | Algal Reef | Pork Import | Election |
| Eligible | 0.20 | -0.01 | -0.15 | 0.02 |
| | (0.19) | (0.28) | (0.17) | (0.18) |
| Positive Treatment | -0.13 | -0.04 | 0.17 | $0.68^{***}$ |
| | (0.17) | (0.27) | (0.17) | (0.18) |
| Negative Treatment | -0.10 | $-0.60^{*}$ | $-0.57^{***}$ | -0.05 |
| | (0.28) | (0.27) | (0.16) | (0.18) |
| Eligible $\times$ Positive Treatment ($\gamma^{\text{Positive}}$) | 0.13 | 0.54 | 0.09 | -0.27 |
| | (0.27) | (0.36) | (0.24) | (0.24) |
| Eligible $\times$ Negative Treatment ($\gamma^{\text{Negative}}$) | $-1.13^{**}$ | 0.02 | 0.04 | 0.04 |
| | (0.36) | (0.37) | (0.28) | (0.25) |
| Constants | $0.51^{+}$ | -0.09 | 0.17 | -0.07 |
| | (0.28) | (0.33) | (0.23) | (0.21) |
| Support Change in Each Treatment Between Eligibility | | | | |
| $\delta + \gamma^{\text{Positive}}$ | 0.33 | $0.53^{*}$ | -0.06 | -0.25 |
| | (0.20) | (0.24) | (0.16) | (0.15) |
| $\delta + \gamma^{\text{Negative}}$ | $-0.92^{**}$ | 0.01 | -0.10 | 0.06 |
| | (0.33) | (0.24) | (0.21) | (0.16) |
| Subjects | 185 | 207 | 392 | 392 |
| Mean of Dep. Var. | 0.072 | -0.188 | 0.031 | 0.012 |
| Pre-treatment Support | 0.001 | 0.105 | -0.056 | -0.031 |
| Post-treatment Support | 0.073 | -0.082 | -0.024 | -0.019 |

*Notes.* (i) Standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ (ii) *Support Change in Each Treatment Between Eligibility* estimates (with Wald estimator) the difference in the support changes in each treatment group between eligible and ineligible subjects. (iii) The education backgrounds (whether the subject studies at a public school, or studies social science), sex, household income, and their favorite political party are controlled.

Table D4: Heterogeneity: split by pre-treatment awareness

| | *Vote Changes:* Post Vote − Pre Vote | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Nuclear Power | Nuclear Power | Algal Reef | Algal Reef | Pork Import | Pork Import | Election | Election |
| Eligible | -0.038 | 0.130 | 0.031 | -0.685$^{***}$ | -0.025 | -0.022 | -0.045 | 0.054 |
| | (0.151) | (0.188) | (0.407) | (0.164) | (0.129) | (0.134) | (0.123) | (0.156) |
| Positive Treatment | 0.025 | 0.047 | -0.183 | -0.488$^{**}$ | 0.068 | 0.340$^{*}$ | 0.275$^{+}$ | 0.402$^{*}$ |
| | (0.185) | (0.140) | (0.293) | (0.184) | (0.133) | (0.153) | (0.139) | (0.163) |
| Negative Treatment | -0.205 | 0.091 | -0.162 | -0.849$^{***}$ | -0.063 | -0.054 | -0.177 | 0.302$^{+}$ |
| | (0.223) | (0.214) | (0.310) | (0.221) | (0.141) | (0.142) | (0.120) | (0.161) |
| Eligible × Positive Treatment | -0.061 | 0.035 | 0.409 | 0.894$^{***}$ | 0.063 | -0.222 | -0.153 | -0.216 |
| | (0.233) | (0.321) | (0.424) | (0.231) | (0.182) | (0.194) | (0.200) | (0.227) |
| Eligible × Negative Treatment | -0.167 | -0.448 | -0.204 | 0.785$^{**}$ | -0.241 | 0.058 | 0.238 | -0.136 |
| | (0.317) | (0.319) | (0.478) | (0.243) | (0.213) | (0.196) | (0.162) | (0.204) |
| Constants | 0.707$^{*}$ | 0.040 | -0.324 | 0.706$^{**}$ | -0.240 | 0.117 | 0.139 | 0.032 |
| | (0.291) | (0.223) | (0.289) | (0.233) | (0.202) | (0.181) | (0.154) | (0.174) |
| Treatment Effect Between Eligibility | | | | | | | | |
| $\delta + \gamma^{\text{Positive}}$ | -0.099 | 0.165 | 0.440$^{*}$ | 0.209 | 0.039 | -0.245$^{+}$ | -0.198 | -0.162 |
| | (0.205) | (0.271) | (0.208) | (0.161) | (0.129) | (0.146) | (0.149) | (0.165) |
| $\delta + \gamma^{\text{Negative}}$ | -0.206 | -0.318 | -0.173 | 0.100 | -0.265 | 0.036 | 0.193$^{*}$ | -0.082 |
| | (0.298) | (0.245) | (0.215) | (0.183) | (0.170) | (0.149) | (0.096) | (0.136) |
| Subjects | 76 | 75 | 55 | 105 | 143 | 182 | 181 | 138 |
| Mean of Dep. Var. | 0.039 | 0.120 | -0.145 | -0.076 | 0.007 | 0.088 | 0.094 | 0.101 |
| Pre-treatment Yea Share | 0.513 | 0.520 | 0.673 | 0.638 | 0.517 | 0.396 | 0.398 | 0.464 |
| Post-treatment Yea Share | 0.553 | 0.640 | 0.527 | 0.562 | 0.524 | 0.484 | 0.492 | 0.565 |
| Awareness | > Median | ≤ Median | > Median | ≤ Median | > Median | ≤ Median | > Median | ≤ Median |

*Notes.* (i) This table split the subjects by their pre-treatment knowledge of each proposition. The odd columns include the subjects whose knowledge is above median, and the even columns include subjects whose knowledge is equal to or below median. (ii) Standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ (iii) *Vote Change in Each Treatment Between Eligibility* estimates (with Wald estimator) the difference in the vote changes in each treatment group between eligible and ineligible subjects. (iv) The education backgrounds (whether the subject studies at a public school, or studies social science), sex, household income, and their favorite political party are controlled.

Table D5: Heterogeneity: split by pre-treatment knowledge

| | *Vote Changes:* Post Vote − Pre Vote | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Nuclear Power | Nuclear Power | Algal Reef | Algal Reef | Pork Import | Pork Import | Election | Election |
| Eligible | 0.017 | -0.014 | -0.361 | -0.471$^{**}$ | -0.161 | 0.024 | -0.101 | 0.031 |
| | (0.193) | (0.168) | (0.432) | (0.171) | (0.180) | (0.117) | (0.141) | (0.144) |
| Positive Treatment | -0.137 | 0.147 | -0.160 | -0.347$^{+}$ | 0.104 | 0.212 | 0.215 | 0.418$^{**}$ |
| | (0.166) | (0.179) | (0.323) | (0.199) | (0.174) | (0.135) | (0.154) | (0.146) |
| Negative Treatment | -0.181 | -0.064 | -0.450 | -0.763$^{**}$ | -0.028 | -0.091 | -0.069 | 0.073 |
| | (0.260) | (0.204) | (0.338) | (0.233) | (0.157) | (0.136) | (0.139) | (0.132) |
| Eligible × Positive Treatment | -0.045 | -0.054 | 0.591 | 0.725$^{**}$ | 0.268 | -0.207 | -0.077 | -0.320 |
| | (0.344) | (0.251) | (0.451) | (0.239) | (0.222) | (0.174) | (0.199) | (0.221) |
| Eligible × Negative Treatment | -0.271 | -0.317 | 0.243 | 0.673$^{*}$ | -0.172 | 0.043 | 0.106 | 0.089 |
| | (0.360) | (0.290) | (0.492) | (0.270) | (0.241) | (0.183) | (0.186) | (0.185) |
| Constants | 0.734$^{+}$ | 0.179 | 0.287 | 0.308 | 0.145 | -0.045 | 0.246 | 0.134 |
| | (0.373) | (0.181) | (0.549) | (0.214) | (0.217) | (0.179) | (0.173) | (0.159) |
| Treatment Effect Between Eligibility | | | | | | | | |
| $\delta + \gamma^{\text{Positive}}$ | -0.028 | -0.068 | 0.229 | 0.254 | 0.107 | -0.183 | -0.178 | -0.289 |
| | (0.295) | (0.187) | (0.221) | (0.174) | (0.140) | (0.132) | (0.135) | (0.182) |
| $\delta + \gamma^{\text{Negative}}$ | -0.254 | -0.331 | -0.118 | 0.202 | -0.332$^{*}$ | 0.067 | 0.005 | 0.120 |
| | (0.316) | (0.232) | (0.234) | (0.212) | (0.162) | (0.147) | (0.115) | (0.116) |
| Subjects | 56 | 95 | 48 | 112 | 117 | 208 | 164 | 155 |
| Mean of Dep. Var. | 0.036 | 0.105 | -0.104 | -0.098 | 0.043 | 0.058 | 0.146 | 0.045 |
| Pre-treatment Yea Share | 0.536 | 0.505 | 0.604 | 0.670 | 0.436 | 0.457 | 0.378 | 0.477 |
| Post-treatment Yea Share | 0.571 | 0.611 | 0.500 | 0.571 | 0.479 | 0.514 | 0.524 | 0.523 |
| Informedness | > Median | ≤ Median | > Median | ≤ Median | > Median | ≤ Median | > Median | ≤ Median |

*Notes.* (i) This table split the subjects by their pre-treatment knowledge of each proposition. The odd columns include the subjects whose knowledge is above median, and the even columns include subjects whose knowledge is equal to or below median. (ii) Standard errors in parentheses. $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$ (iii) *Vote Change in Each Treatment Between Eligibility* estimates (with Wald estimator) the difference in the vote changes in each treatment group between eligible and ineligible subjects. (iv) The education backgrounds (whether the subject studies at a public school, or studies social science), sex, household income, and their favorite political party are controlled.

# E. Appendix Figures for Chapter 2

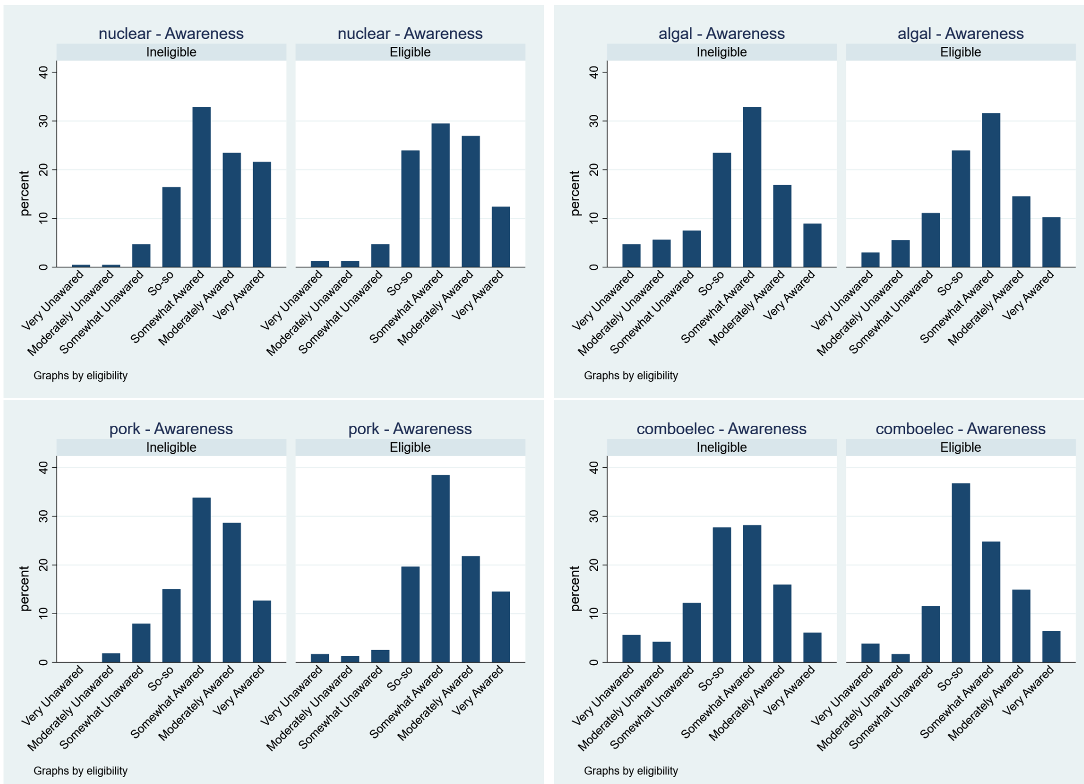



Figure E1: Balancedness check: awareness of the propositions

*Notes.* The figures summarize the responses in each of the following questions: "how much are you aware of this proposition?" The questions were asked in the Referendum Survey, which was conducted right after the referendum. Each panel represents one proposition, split by eligibility. Only the estimation sample is included in this figure.

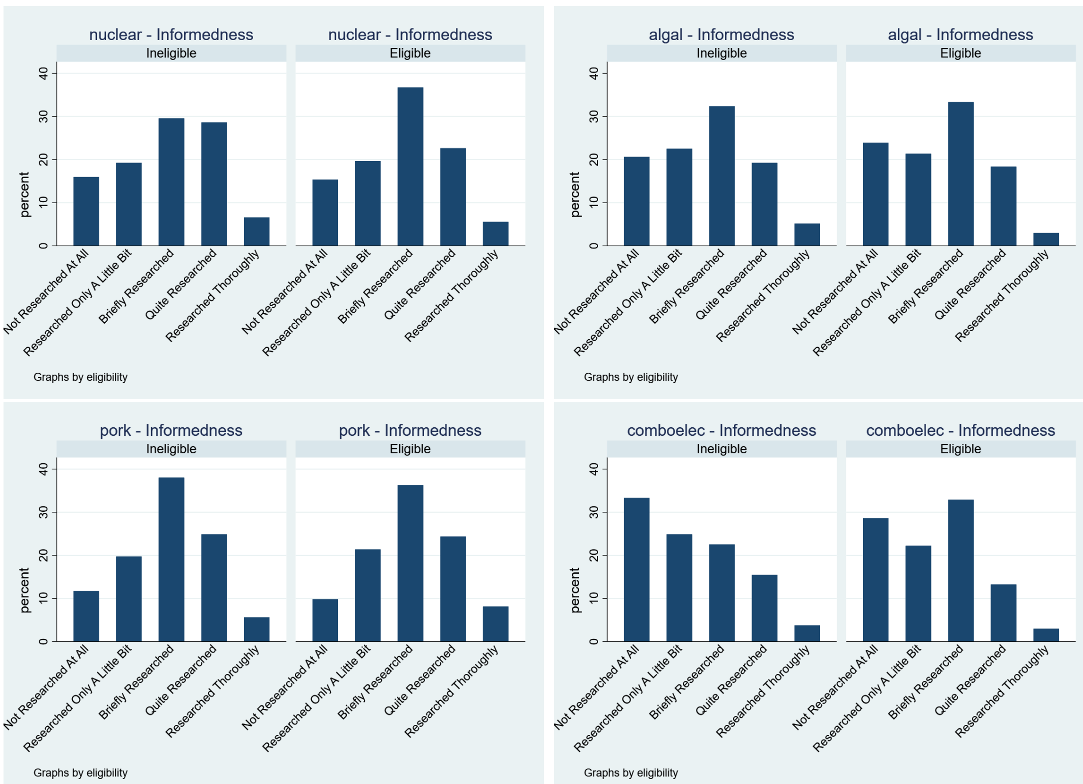



Figure E2: Balancedness check: informedness about the propositions

*Notes.* The figures summarize the responses in each of the following questions: "how much do you know about this proposition?" The questions were asked in the Referendum Survey, which was conducted right after the referendum. Each panel represents one proposition, split by eligibility. Only the estimation sample is included in this figure.

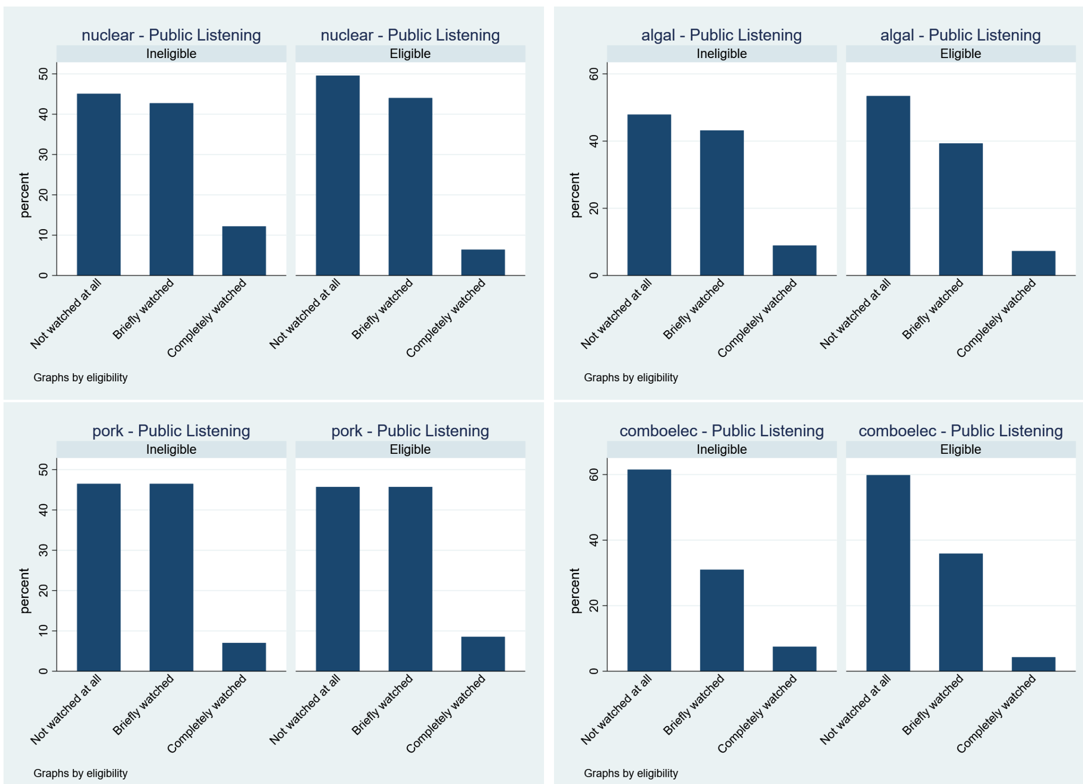



Figure E3: Balancedness check: whether subjects watched the public hearing

*Notes.* The figures summarize the responses in each of the following questions: "have you watch the television broadcast of the public hearing of this proposition?" The questions were asked in the Referendum Survey, which was conducted right after the referendum. Each panel represents one proposition, split by eligibility. Only the estimation sample is included in this figure.

# F. Appendix Tables for Chapter 3

Table F1: List of Reports

| Report | Majority | Difference | Proportion | Count | Sequence (corresponding count) |
|---|---|---|---|---|---|
| 1 | Orange/Green | | | | |
| 2 | | ± 1 | | | |
| 3 | | ± 3 | | | |
| 4 | | ± 5 | | | |
| 5 | | ± 9 | | | |
| 6 | | | 0%/100% | | |
| 7 | | | 20%/80% | | |
| 8 | | | 33%/67% | | |
| 9 | | | 40%/60% | | |
| 10 | | | | 3-0 | |
| 11 | | | | 5-0 | |
| 12 | | | | 9-0 | |
| 13 | | | | 2-1 | |
| 14 | | | | 4-1 | |
| 15 | | | | 3-2 | |
| 16 | | | | 12-3 | |
| 17 | | | | 10-5 | |
| 18 | | | | 9-6 | |
| 19 | | | | | ooo (3-0) |
| 20 | | | | | ogo (2-1) |
| 21 | | | | | oog (2-1) |
| 22 | | | | | ooooo (5-0) |
| 23 | | | | | oooog (4-1) |
| 24 | | | | | oogoo (4-1) |
| 25 | | | | | ooogg (3-2) |
| 26 | | | | | ogogo (3-2) |
| 27 | | | | | ooooooooo (9-0) |
| 28 | | | | | ooooooooooooggg (12-3) |
| 29 | | | | | oogoooogoooogoo (12-3) |
| 30 | | | | | ooooooooooggggg (10-5) |
| 31 | | | | | ogoogoogoogoogo (10-5) |
| 32 | | | | | ooooooooogggggg (9-6) |
| 33 | | | | | ogogoogogoogogo (9-6) |

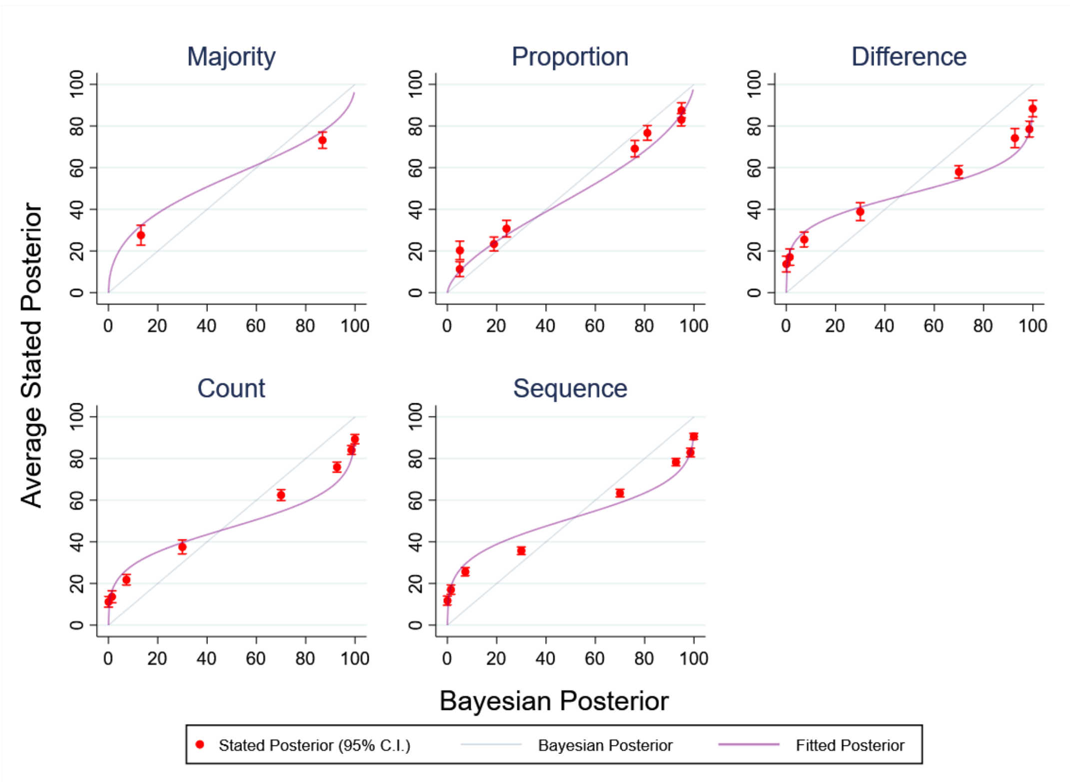
*Notes.* The list shows the preassigned reports implemented in the experiment. In *Majority*, the subjects either read "more orrange" or "more green". In *Difference*, the listed reports represent the difference the subjects see; for instance, "± 3" means one color has 3 more balls than the other. In *Proportion*, they see the proportions of different-colored balls; for instance, "33%/67%" means 33% of balls are in one color and 67% are in the other color. In *Count*, the listed reports represent the counts the subjects see; for instance, "2-1" means 2 balls in one color and 1 ball in the other. In *Sequence*, the listed reports represent the specific sequence the subjects see; for instance, "ogo" means the subject sees a sequence of "orange-green-orange" balls. From the same report, the majority is randomly assigned. For instance, when a subject is assigned Report 20, she may be assigned "oro" or "ror" with same probabilities.

Table F2: Estimated Responsiveness to changes in Likelihood Ratio with Interaction

| | (1) All Five reports $ln\left(\frac{\pi(Box\ O\vert S_{\gamma_R})}{\pi(Box\ G\vert S_{\gamma_R})}\right)$ | (2) Without *Majority* $ln\left(\frac{\pi(Box\ O\vert S_{\gamma_R})}{\pi(Box\ G\vert S_{\gamma_R})}\right)$ | (3) *Difference* vs *Count* vs *Sequence* $ln\left(\frac{\pi(Box\ O\vert S_{\gamma_R})}{\pi(Box\ G\vert S_{\gamma_R})}\right)$ |
|---|---|---|---|
| $ln\left(\frac{p(Box\ O\vert S_{\gamma_R})}{p(Box\ G\vert S_{\gamma_R})}\right)$ | 0.543*** | 0.674*** | 0.313*** |
| | (0.0536) | (0.0325) | (0.0180) |
| *Proportion* | -0.0527 | | |
| | (0.111) | | |
| *Difference* | -0.131 | -0.0785 | |
| | (0.108) | (0.0733) | |
| *Count* | -0.0801 | -0.0274 | 0.0510 |
| | (0.101) | (0.0541) | (0.0584) |
| *Sequence* | -0.0206 | 0.0320 | 0.110* |
| | (0.0995) | (0.0552) | (0.0559) |
| *Proportion* $\times ln\left(\frac{p(Box\ O\vert S_{\gamma_R})}{p(Box\ G\vert S_{\gamma_R})}\right)$ | 0.131*** | | |
| | (0.0467) | | |
| *Difference* $\times ln\left(\frac{p(Box\ O\vert S_{\gamma_R})}{p(Box\ G\vert S_{\gamma_R})}\right)$ | −0.230*** | −0.361*** | |
| | (0.0480) | (0.0246) | |
| *Count* $\times ln\left(\frac{p(Box\ O\vert S_{\gamma_R})}{p(Box\ G\vert S_{\gamma_R})}\right)$ | −0.187*** | −0.317*** | 0.0431*** |
| | (0.0499) | (0.0249) | (0.0132) |
| *Sequence* $\times ln\left(\frac{p(Box\ O\vert S_{\gamma_R})}{p(Box\ G\vert S_{\gamma_R})}\right)$ | −0.180*** | −0.310*** | 0.0498*** |
| | (0.0500) | (0.0227) | (0.0124) |
| Constant | -0.0396 | -0.0963 | -0.140 |
| | (0.131) | (0.0983) | (0.100) |
| N | 3205 | 3108 | 2718 |

*Notes.* $***$ $p$-value $< 0.01$, $**$ $p$-value $< 0.05$ and $*$ $p$-value $< 0.1$. Standard errors are clustered at the subject level with gender and grade as controls.

# G. Appendix Figures for Chapter 3




*Note:* The stated posteriors are plotted against Bayesian posteriors by reports. On each point, we plot the 95% confidence interval. The blue lines represent the 45-degree line as the Bayesian benchmark. The fitted posterior is derived from Equation (3.7), where the coefficients are taken from Table 3.2. Include the linear approximation of the stated beliefs of 0% and 100%.

Figure G1: Stated Belief and Bayesian Benchmark across Reports

## G.1 Report-Whatever-You-See Heuristics

It is possible that, instead of making better use of the proportion information, subjects might just naively report whatever they saw under Proportion. If the majority tends to do so and the rest performs in the identical way as under Count and Sequence, the naive resemblance could result in the finding that the stated beliefs are on average less compressed towards 50:50. We address this concern by classifying stated beliefs under

Report Proportion into two types according to whether it is within $\pm$ 5% of the proportion information provided. We find that the majority is out of the proportion $\pm$ 5%: 67% are out of proportion $\pm$ 5%, and 33% of stated beliefs are within proportion $\pm$ 5%. To further explore whether the out-of-proportion-$\pm$ 5% type is more compressed towards 50:50 or closer to the Bayesian Benchmark, We plot the average stated posteriors against Bayesian posteriors under the Report Proportion and separate them by the two types in Figure G2. For those out of proportion $\pm$ 5%, the stated beliefs are closer to the Bayesian benchmark than to 50:50. This result suggests that, instead of naively stating whatever subjects saw under Report Proportion, the majority indeed makes better use of the information under Proportion.

One possible explanation of the subjects' better performance under Proportion is that the subjects are naively reporting the proportions they observe, and it naturally makes the estimated sensitivity close to one. We provide two pieces of evidence against this explanation. First, 67% of our subjects do *not* state their posterior beliefs close (plus or minus 0.05) to the actual proportion they see. Second, when we plot the stated posteriors against the Bayesian posteriors, the observations that are close to the presented proportions are showing more deviated (with respect to Bayesian) sensitivity than those are not close. Please see Figure G2 for more details.

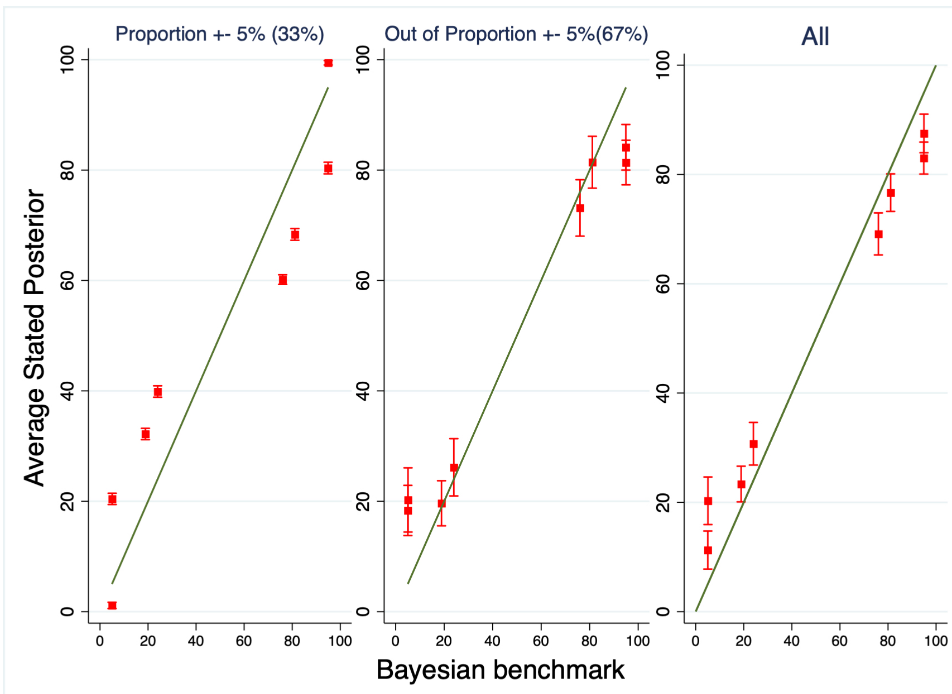



Figure G2: Stated Beliefs under Report Proportion

*Note:* In the left and middle panels, we plot the average stated posteriors against Bayesian posteriors under Report Proportion and separate them by whether the stated belief is within proportion ±5%. The percentage in the bracket is the fraction of stated beliefs which belong to the type. The right panel plots the pooled results. On each point, we plot the 95% confidence interval.

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