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1. Introduction

Information provision experiments have emerged as an important tool for social scientists, providing ample opportunities for a better understanding of how beliefs shape human behavior. The key feature of information provision experiments is that they offer researchers the opportunity to flexibly change the information sets available to respondents, making it possible to exogenously shift people's beliefs and perceived constraints.

One of the most compelling applications of these experiments is in generating exogenous variation in perceptions of real-world scenarios, thereby enabling the evaluation of various policy-relevant questions. This approach is particularly useful in areas where direct manipulation of real-world phenomena is unfeasible:
For instance, in labor economics, researchers can't alter actual outside options of earners but can manipulate perceptions of outside options to gauge their impact (Jäger et al., 2024). Similarly, when studying investors' investment decisions, altering actual returns of investment opportunities is not possible, but modifying public perceptions about them is feasible and insightful (Haaland & Næss, 2023; Laudenbach et al., 2023). Another example is the application of information experiments to understand social norms. For instance, while researchers cannot directly change social norms, they can explore their causal effects on behavior by altering perceived norms (Bursztyn, González and Yanagizawa-Drott, 2020). Similarly, perceptions about macroeconomic factors, such as the likelihood of a recession or future home price developments, can be experimentally varied, offering insights into their impact on economic decisions (Roth & Wohlfart, 2020; Chopra et al., 2024).

The significance of information provision experiments has been surging, as evidenced by their increasing presence in leading social science journals (Haaland et al., 2023). This article aims to review this burgeoning field, with a particular focus

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on methodological nuances and recent trends. This review article builds on Haaland et al., 2023 and other recent work on survey experiments (Fuster & Zafar, 2023; Stantcheva, 2023; Capozza et al., 2022).

The review proceeds as follows: In Section 2, we define information provision experiments. In Section 3, we discuss various methods to measure beliefs. Section 4 discusses designing effective information treatments, while Section 5 focuses on measuring belief updating and associated challenges. Section 6 addresses the issue of experimenter demand effects and how to mitigate them. Finally, Section 7 offers directions for future research in the domain of information provision experiments and belief formation.

2. Definition of Information Provision Experiments

Information provision experiments in social sciences are designed to study how people's decisions and beliefs are influenced by the information they receive. In these experiments, researchers provide participants with specific information and then observe and analyze how this alters their beliefs, attitudes, and subsequent decisions. The basic concept hinges on the assumption that access to, or the lack of, certain information can significantly impact decision-making processes. These experiments help in understanding how people integrate new information into their existing knowledge base and how this affects their behavior in various economic, political, and social contexts.

3. Measuring Beliefs

Understanding how information affects beliefs and economic behavior is often essential to advance both theory and policy-making. Information provision experiments are a flexible tool to achieve this. In this section, we synthesize the current literature on measuring beliefs in these experiments, focusing on both prior and posterior belief elicitation, the nature of belief measurement, and the utility of hypothetical vignettes.

Eliciting Prior and Posterior Beliefs: The elicitation of prior beliefs is crucial for estimating heterogeneous treatment effects based on these beliefs. Cruces et al. (2013) exemplify this by demonstrating how individuals with varying prior beliefs about their income position respond differently to information. Moreover, the elicitation of prior beliefs enhances statistical power for detecting treatment effects (Clifford et al., 2021) and aids in estimating learning rates (Roth et al., 2022a). Conversely, eliciting posterior beliefs is essential to understand the first stage of information effect and assess trust or attention to the provided information.

However, measuring both priors and posteriors can induce experimenter demand effects or consistency bias. Roth & Wohlfart (2020) and Clifford et al. (2021) provide empirical evidence that these potential biases might not significantly impact the results, but it is still good practice to supplement posterior beliefs with other types of post-treatment belief measures that are not mechanically related to the prior belief elicitation (e.g., by eliciting post-treatment beliefs about future outcomes).

Belief Measurement Techniques: Beliefs can be measured qualitatively, quantitatively, or probabilistically. Qualitative measures, while easy for respondents to understand, face challenges in interpersonal comparability and theoretical ambiguity in belief updates (Manski, 2017; Gaines et al., 2007). Quantitative point estimates of beliefs offer comparability but may not capture respondents' uncertainty about outcomes. Probabilistic beliefs, although comprehensive and comparable, are often challenging for a large part of the population to grasp (Kahneman & Tversky, 1974). The right complexity of the belief measurement depends on the context, such as survey length and sophistication of the survey population.

Confidence and Belief Measurement: Recently, there has been an increased focus on directly measuring individuals' uncertainty, particularly within abstract decision-making, belief updating tasks, and survey expectations. Enke & Graeber (2023) introduce the concept of cognitive uncertainty to measure perceived uncertainty about optimal action and illustrate its predictive power in unifying various decision-making anomalies.

Benchmarks and Framing in Belief Elicitation: Objective external benchmarks for belief elicitation enhance comparability and reduce interpretation heterogeneity. For instance, Haaland & Roth (2023) measure beliefs about the results of a study analyzing callback rates of job applicants with white-sounding vs. black-sounding names. Additionally, careful framing of questions, like providing anchors, can significantly reduce measurement error (Ansolabehere et al., 2013).

Mitigating Measurement Error: Multiple measurements using qualitative and quantitative approaches can help mitigate classical measurement errors (Gillen et al., 2019). However, balancing cognitive demand against survey fatigue is crucial in this approach.

Incentivizing Accurate Belief Elicitation: Incentives in belief elicitation, particularly with objective benchmarks, can promote truthful responses and reduce partisan bias (Prior et al., 2015; Bullock et al., 2015). However, the impact of incentives varies across contexts, with limited effects in non-political domains (Roth & Wohlfart, 2020; Allcott et al., 2020).

4. How to Design Information Treatments

In this section, we discuss the most important factors to consider when designing information treatments.

Types of Information

Quantitative Information: Employing quantitative information like statistics and forecasts enriches survey experiments, aiding the interpretation of results within theoretical frameworks (Kuziemko et al., 2015; Roth et al., 2022b). With elicited priors and posteriors, numerical data allows for understanding and facilitates the calculation of learning rates (Armantier et al., 2016; Roth & Wohlfahrt, 2020). Often, researchers provide information about the behavior of others and use a random subset of respondents to assess the influence of social information on individual decisions (Bursztyn, González and Yanagizawa-Drott, 2020; Coibion et al., 2021).

Anecdotal Evidence, Stories, and Narratives: Another vital approach relies on qualitative anecdotes, stories, or narratives. They provide rich, case study-like information distinct from statistical data. This approach, though less common, holds potential for impactful future research (Bernard et al., 2014; Riley, 2022). For example, structured and open-ended survey questions are used to measure US households and experts' subjective models about the propagation mechanism of macroeconomic shocks (Andre, Pizzinelli et al., 2022). Andre, Haaland, et al. (2022) study how the provision of different narratives about the rise of inflation alters inflation expectations. In the context of narratives, Bursztyn et al. (2023) explore how rationales supporting dissenters, such as credible scientific evidence, can facilitate public expression and reduce social sanctions on social media. Graeber, Roth, and Zimmermann (2023) investigate how the type of information (story vs. statistic) influences selective memory. Graeber, Noy, and Roth (2023) study how people learn from qualitative voice messages and how this learning is altered through the process of information transmission.

Presentation and Credibility

Presentation: Effective information presentation should be concise and neutrally framed, sometimes supplemented with graphical illustrations for clarity (Roth & Wohlfart, 2020).

Credibility of Sources: The trustworthiness of the information source is vital. Studies show that inconsistency in information can reduce trust and belief revision (Rafkin et al., 2021). To maximize belief change, researchers must balance providing substantial information shocks from people's prior and maintaining the information's credibility, as overly extreme information may reduce perceived trustworthiness (Gentzkow & Shapiro, 2006).

Sender characteristics: The identity of the information provider can significantly influence the effectiveness of the message. Studies show varying effects based on the sender's characteristics, such as race or expertise (Alsan & Eichmeyer, 2024; Korlyakova, 2021). The sender's perceived bias affects the message's acceptance and impact (Cavallo et al., 2016); using direct questions at the end of the survey on the credibility and accuracy of the information is a good practice to better understand these effects.

Distinguishing Priming from Information

A significant challenge in information experiments is distinguishing the impact of attention from actual belief changes: Conlon (2024) illustrates that information not only shifts beliefs but also redirects attention. Strategies to isolate the effects of belief changes include eliciting prior beliefs, follow-up studies, and using active control groups, which we discuss below.

Active vs. Passive Control

A key design decision concerns the choice between an active control group or a passive control group. In a passive control group design, respondents in the control group receive no information, while in an active control group design all respondents receive some (but different) information. Active control groups, which have been increasingly employed in recent years (Bottan & Perez-Truglia, 2022; Roth & Wohlfart, 2020; Hager et al., 2022; Roth et al., 2022b) can offer more robust insights into causal effects. They enable broader identification of causal effects across individuals with varying accuracy in prior beliefs and help control for side effects such as uncertainty reduction and emotional responses. However, passive control groups offer clearer interpretation of pre-treatment beliefs and are sometimes necessary to avoid deception or when specific research questions demand a comparison to a no-information scenario.

5. Measuring Belief Updating

In the evolving realm of information treatment studies, it is imperative to measure a diverse array of beliefs to grasp the theoretical mechanisms at play. This article delves into methodologies to bypass issues like numerical anchoring and underscores the necessity of measuring beliefs concerning the provided information.

Numerical Anchoring and its Mitigation: Numerical anchoring poses a significant methodological concern, especially in studies with quantitative post-treatment outcomes. To counter this, employing irrelevant numerical anchors to test their impact on posterior beliefs can be beneficial, as demonstrated by Coibion et al. (2020). Additionally, measuring beliefs using different quantitative scales and additionally using qualitative belief measures can significantly reduce concerns about anchoring effects.

The Role of Follow-Up Surveys: Follow-up surveys are crucial for assessing the persistence of information effects on beliefs and behaviors, mitigating short-lived phenomena like numerical anchoring and consistency bias. Pioneers in this method, like Kuziemko et al. (2015), have showcased its effectiveness. The interval between initial and follow-up surveys is a critical decision, balancing the need for persistence testing against respondent recontact rates.

Assessing Beliefs about Information: A deeper understanding of information treatment effects can be achieved by measuring trust and other beliefs about the provided information. However, this may introduce experimenter demand effects, which can be mitigated by eliciting incentivized measures for the willingness to pay for the information.

Cross-Learning Challenges: Information provision treatments often lead to cross-learning in which respondents update their beliefs about variables not included in the information treatment. For instance, respondents who receive information about the labor market impacts of immigrants might also update their beliefs about the fiscal burden of immigration (Haaland & Roth, 2020). This phenomenon complicates the interpretation of effects. To tackle this, researchers can provide uniform information about other variables to both control and treatment groups, though this approach might dilute the focus on the primary information. It is crucial to include measures for beliefs about other potentially affected variables to detect and understand the extent and implications of cross-learning. Chopra et al. (2024) provide evidence on cross-learning as they found in a follow-up survey that participants updated not only their housing market beliefs, which were the subject of the information provision, but also their expectations of other macroeconomic variables like future inflation. To address these cross-learning effects, Chopra et al. (2024) conducted an additional experiment: Here, they fixed beliefs at the targeted variable. In this subsequent study, detailed cross-randomized narratives, naming either demand side or supply side factors in the housing market, were cited as the main factor underlying their forecast to control the scope of cross-learning.

To conclude, robustly measuring belief updating requires a broad strategy that includes addressing numerical anchoring, understanding persistence, evaluating trust in information, and addressing potential cross-learning effects. These methods enrich our comprehension of how information treatments influence beliefs, preferences, and behaviors, offering invaluable insights into belief formation and modification mechanics.

6. Dealing with Experimenter Demand Effects

Within social science research, the phenomenon of experimenter demand effects poses a significant challenge. These effects occur when participants in an experiment alter their behavior not based on the treatment itself but due to their perceptions of what the experimenter expects or desires (Zizzo, 2010; de Quidt et al., 2018; Mummolo & Peterson, 2019). This can lead to biased results, as it becomes difficult to discern whether outcomes are due to the treatment or the participants' desire to conform to perceived expectations.

Recent empirical evidence suggests that while the quantitative impact of experimenter demand effects might be limited in online surveys across some domains, the problem persists, particularly in settings where treatment effects could be confounded by participants making differential inferences about the experimenter's expectations (de Quidt et al., 2018; Mummolo & Peterson, 2019). Several strategies have been proposed and implemented to address this issue with varying degrees of success.

Obfuscated Follow-Ups: Haaland & Roth (2020; 2023) introduced the concept of 'obfuscated follow-ups.' This approach involves conducting follow-up studies with the same respondents as in the initial experiment but presenting these follow-ups as independent studies. In the obfuscated follow-up study, where no treatment is applied, concerns about varying responses or expectations (differential experimenter demand) between treatment and control groups are mitigated. The effectiveness of this approach hinges on the respondents not realizing the connection between the follow-up and the main study. It is, therefore, best practice to include several elements to actively hide the connection between the studies, such as using different consent forms and survey layouts.

Anonymity: Anonymity in responses has been shown to be an effective tool against experimenter demand effects (Hoffman et al., 1994). In contexts such as policy preference experiments, researchers have used anonymous online petitions to reduce the influence of experimenter expectations on participant responses (Grigorieff et al., 2020).

Incentivized Outcomes: Using incentivized outcomes in survey experiments is a growing trend. This involves eliciting responses or actions with real monetary consequences under the presumption that demand effects should be lower in tasks involving real stakes (Grigorieff et al., 2020; Roth et al., 2022a).

Field Outcomes: Linking experimental treatments to natural outcomes in the field, such as job offer acceptance or credit card debt repayment, provides unobtrusive behavioral data in a natural setting (Bursztyn, González and Yanagizawa-Drott, 2020; Finkelstein & Notowidigdo, 2019; Haaland & Næss, 2023; Laudenbach et al., 2023; Chopra et al., 2024). In these settings, experimenter demand effects are often negligible, as participants may be unaware they are part of an experiment and it is typically very costly to change behavior. It is, for instance, not very likely that respondents will change their actual investment portfolio trying to please a researcher (Haaland & Næss, 2023; Laudenbach et al., 2023)

Neutral Framing: Adopting a neutral framing of experimental instructions can minimize the relevance of experimenter demand effects. This involves making the purpose of the experiment less transparent and reducing the focus on the experimenter's expectations (Bursztyn, Egorov & Fiorin, 2020; Chopra et al., 2023).

Obfuscated Information Treatments: Obfuscating the purpose of the study by providing additional irrelevant information or tasks can help mitigate experimenter demand effects. This could involve giving participants an unrelated reason for receiving the information of interest (Facchini et al., 2022).

Demand Treatments: Using demand treatments, as proposed by de Quidt et al. (2018), can measure the sensitivity of behavior and self-reports to explicit signals about the experimenter's expectations. This involves telling respondents that certain behaviors are expected from them, thus bounding the natural action.

Measuring Beliefs about the Study Purpose: Measuring participants' beliefs about the study purpose can ascertain the extent to which demand effects might influence behavior. Studies usually find that respondents have quite diffuse and uncertain beliefs about the study purpose (see e.g., Chopra et al., 2023; Jäger et al., 2024).

Summary: In summary, while recent evidence indicates that the quantitative importance of demand effects may be limited in online experiments in certain domains, their significance can vary considerably across different settings. Demand effects can be a notable concern, particularly in sensitive domains where participants may be inclined to please the experimenter. Therefore, employing a combination of the strategies mentioned above is considered best practice in experimental design to mitigate the potential impact of experimenter demand effects.

7. Directions for future research

This review has documented that information provision experiments are a powerful tool for studying beliefs and economic behavior. While they have become increasingly popular over the last few years, there are still ample opportunities to break new ground in research with these types of experiments.

Exploring how individuals interpret and update their beliefs from different types of qualitative information is a particularly promising direction for future research. For instance, understanding the specific characteristics of storytelling that most effectively facilitate learning remains an open question. The nuances of language, tone, and style in these formats can greatly influence the interpretation of qualitative information.

Moreover, exploring the attentional foundations of expectation formation (for example, Bordalo et al., 2023a;b; Conlon, 2024; Link et al., 2023) stands as another underexplored and promising area for future research. This field examines how individuals form expectations based on the information they attend to and how these expectations influence their decision-making and behavior. By better understanding these processes, researchers can contribute significantly to fields such as psychology, marketing, economics, and behavioral sciences.

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