From Informational Beliefs to Complex Political Attitudes: A Bayesian Analysis of American Public Opinion on the Affordable Care Act

by

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ABSTRACT

It has long been assumed that the formation of individuals' attitudes toward a complex attitude object should reflect an integration process whereby individuals evaluate different constituent parts of the attitude object based on the information they have about these components and synthesize these evaluations to render a summary judgment. To what extent this expectation is true, however, remains a question to be answered. Leveraging a nationally representative survey on American public attitudes toward the Patient Protection and Affordable Care Act of 2010, this project investigated how a multitude of informational beliefs about what the law is comprised of, the level of certainty with which individuals hold these beliefs, and evaluations of corresponding provisions of the law, collectively shaped Americans' overall attitude toward this important and highly contentious piece of legislation. Using innovative Bayesian modeling techniques with Markov Chain Monte Carlo methods, this project successfully established a model where beliefs and evaluations associated with different attributes of an attitude object were presumed to have structurally similar relations with the overall attitude, and the variations in the effects of distinct beliefs and evaluations were determined by varying importance levels of different attributes of the attitude object.

Furthermore, through a series of counterfactual simulations leveraging Bayesian linear regression and logistic regression models, this project identified the pivotal roles of belief accuracy and belief certainty in the process of political attitude formation. Possessing correct beliefs about what the law would and would not do improved the law's overall favorability.

Holding correct beliefs with full certainty could even transform a slightly negative overall attitude toward the law to a slightly positive one. However, the counterfactual simulations also revealed that the increase in belief certainty resulted in a tremendous increase in attitude extremity. The size of the "neutral" group diminished while the group of those who were expected to express strong preferences (either favor or oppose) expanded enormously. The improvement in individuals' state of information (i.e., belief accuracy and belief certainty) led to both more favorable and more polarized overall attitudes toward the law. On this highly contentious public policy where there is persistent partisan divide, only a small portion of the partisan attitudinal gap could be accounted for by the state of information about and evaluations of distinct components of the law, while a large portion of the partisan discrepancy might reflect some more profound and inherent partisan considerations.

CHAPTER 1

An Informed Citizenry

> The functionaries of every government have propensities to command at will the liberty and property of their constituents. There is no safe deposit for these but with the people themselves; nor can they be safe with them without information. Where the press is free, and every man able to read, all is safe.
>
> —— Thomas Jefferson

An informed citizenry is the cornerstone of contemporary democracy. From Thomas Jefferson's (1816) powerful assertion as quoted above, to Alexis de Tocqueville's (1835/2000) observation on how American democracy thrived in the cultivation of citizenship, to John Dewey's (1916) exploration of how education prepared citizens with knowledge, values, and skills to act for public benefits, it is almost a tenet that information is necessary for citizens to meaningfully participate in the political process, actively engage in public debates and discussions, critically evaluate policies, vote for candidates who best align with their interests, hold elected officials accountable, and make decisions and choices that can best promote the common good and protect democracy.

Perhaps because we resolutely hold onto the belief that an informed citizenry is a normative ideal, and because information is at the very center of constructing this ideal for effective democratic participation, understanding the state of citizens' information has long been at the crux of political communication and public opinion research. This is particularly evident from two different research traditions. First, researchers have long documented a knowledge deficit among American voters and lamented how political ignorance prevented people from making consistent, well-informed choices (e.g., Bartels, 1996; Bennett, 1989; Campbell et al., 1960; Delli Carpini & Keeter, 1996; Fowler & Margolis, 2014; Gilens, 2001). Second, researchers have worried that disinformation and misinformation could taint citizens' cognitions, bias their attitudes, and lead them to make decisions with damaging consequences, which is especially alarming in the era of social media (e.g., Bennett & Livingston, 2018; Del Vicario et al., 2016; Edelman, 2001; Freelon & Wells, 2020; Jerit & Zhao, 2020; Kuklinski et al., 2000). Tons of money and resources from both public and private sectors have been poured into the fight against "fake news," which is ostensibly ubiquitous according to both populist politicians and professional news media (Egelhofer & Lecheler, 2019; Farkas & Schou, 2018; Lazer et al., 2018; Ross & Rivers, 2018), even though those decrying the information environment do not necessarily agree with one another on what is or who produced "fake news."

These two research traditions, as well as the endeavor fighting against "fake news," operate on a shared assumption, namely, that individuals' attitude formation and decision-making largely depend on relevant information that they receive and believe (e.g., Anderson, 1973; Bettman et al., 1975; Fishbein & Azjen, 1975, 2010; Kuklinski et al., 2000; McGuire, 1968, 1969; Wegener & Carlston, 2005; Zaller, 1992). This claim, however plausible and intuitive it might sound, should not be treated as a given. For one, if the knowledge about a presidential candidate's view on the environment or immigration plays no role when the electorate considers whom to vote for, whether citizens have this piece of knowledge may prove irrelevant. Similarly, if information about the safety or effectiveness of vaccines does not influence decisions on whether to vaccinate, the accuracy of such information is inconsequential. If information is not part of the calculus, endeavors to increase political awareness and to address inaccuracies might divert valuable resources that could be better expended elsewhere in public communication and education.

In fact, scholars have noted a variety of circumstances where information might not be relevant in attitude formation and decision-making processes. This could occur either because individuals may leverage heuristic cues rather than substantive information to make their decisions (e.g., Chaiken, 1980; Lau & Redlawsk, 2001; Lupia, 1994), or because their stated beliefs are not based on factual understandings, but instead reflect rationalizations from political preferences and thus are not the causes but the consequences of the attitudes in question (Taber & Lodge, 2006). Indeed, at times the attitudes and opinions that people express are overtly incompatible with indisputable information which they are well aware of, which makes it seems as if the only plausible explanation is that their expressed attitude is not based on information at all (e.g., Bullock & Lenz, 2019; Ross & Levy, 2023; Schaffner & Luks, 2018). Therefore, to either confirm or rebut the influence of information in shaping people's political attitudes, we need to better understand the attitude formation process and assess the role of information in it.

Do people use information the way that scholars think they should?

Just as we believe that an informed citizenry is a normative ideal, many researchers also have a normative expectation for how information should be leveraged by citizens in the political attitude formation process. We hope that citizens will seek out information on a variety of issues pertaining to civic life from diverse and reliable sources. As they peruse information, citizens should strive to understand the context, background, substance, and implications of the content that they encounter. They are expected to assess the quality of different pieces of information, scrutinize the credibility of sources, and check for potential biases, inconsistencies, and inaccuracies. They should then consolidate the information that they have gathered and evaluated to develop well-rounded perspectives by thoroughly considering various aspects of the issues. In the meantime, they should also engage in meaningful and respectful discussions with other citizens who might hold differing views from themselves, which could further enhance their own understanding of those issues. By synthesizing the information and weighing the pros and cons, citizens can eventually form evidence-based, well-reasoned attitudes on those issues. And if every political attitude could be formed in such an ideal manner, we would eventually have a healthy, robust, and sustainable democracy.

This ideal is probably too far-fetched. Most people do not have the time, interest, or resources to become deeply engaged with politics. They have jobs to do, bills to pay, families to care for, and personal interests to pursue. As a result, politics often remains a peripheral concern and it is almost irrational to expect that citizens in the real world would gather and evaluate information on public affairs and politics with such rigor and diligence (Lupia, 2016). And even if we set aside the fact that most people would never be so intellectually motivated and politically sophisticated, and focus solely on the relatively limited amount of political information that average citizens possess, to what extent their political attitude formation actually reflects this ideal process of information synthesis and integration is not thoroughly investigated or well-established.

To be sure, examining how information shapes individuals' expressed attitudes has a long history in literatures across the fields of social psychology, political science, and communication studies (e.g., Albarracín et al., 2005; Barnes et al., 2018; Chan et al, 2017; Florence, 1975; MacKuen,1984; Munro & Ditto, 1997; Ranney & Clark, 2016; Zaller, 1992). Despite the abundance of prior research, however, the process whereby political information and media messages shape public opinion is still not well understood. This gap in what seems like a foundational matter to many academic disciplines stems neither from a lack of good theory nor from failures of previous research, but instead from the information environment itself and the inherent challenges of our methods. Put simply, individuals receive numerous pieces of complex information from different media or interpersonal sources every day that they are expected to sort through, evaluate, and distill into summary judgments about key issues that they can use to guide their policy preferences or voting choices (Bimber, 2003; Schmitt et al., 2018; York, 2013). This task is intrinsically challenging, and the information underlying those attitudes comes bundled with additional cues about factors like sources, importance, and constituencies of the messages that can shape which pieces of information are used and how they are processed (e.g., Arceneaux & Johnson, 2013; Chaiken, 1980; Metzger et al., 2010; Petty & Cacioppo, 1984). Experiments and surveys that focus on at most a few parts of this process cannot capture these factors fully and often come to diverging conclusions about their relevance (e.g., minimal vs. maximal effects; Hovland, 1954).

Experimental studies often fall short of providing a holistic picture of the dynamics between information and complex attitudes. Most experimental studies involve identifying possible attitudinal changes induced by information interventions (e.g., Grigorieff et al., 2020; Ranney & Clark, 2016). The typical design of this type of studies offers one piece of new information at a time, with the aim of either providing a new fact or correcting an existing misperception, and tests whether exposure to this new piece of information would induce a corresponding change in the expressed attitude. Whereas this type of design allows a causal claim to be made, it does not provide a full picture of the attitude formation process because the possible correlations between different pieces of information are not adequately taken into account. For example, individuals' attitudes toward a presidential candidate might be related to information on the candidate's competency, experience, personality, and morality, as well as the candidate's policy stands on a variety of issues ranging from health care and education to national defense and diplomacy. A typical experimental design could allow us to determine whether encountering one piece of new information with regard to any of these specific attributes or policies will or will not impact the favorability of this candidate, yet it cannot facilitate an overall evaluation of how different pieces of information about different attributes and policy stands of the candidate collectively shape an individual's attitude toward this candidate. Experimenters rarely change multiple pieces of information at a time because that would prevent them from making a causal claim (as is apparent in the current debate about comparing experimental effects in conjoint studies, Bansak et al., 2021). Yet most attitude objects, if not all, have multiple facets and attributes, and the overall attitude, if based on information, is unlikely to be determined by one single piece (Crano & Lyrintzis, 2015; Krosnick & Smith, 1994). Correspondingly, beliefs in the real world are almost never updated one at a time, yet this type of studies relies on the notion that there is some sort of pure intervention that could shift one belief without altering the constellation of related beliefs (e.g., by shaping how likely other things are to be true or how credible information providers might be.) And encountering this single piece of information in a research environment without other cues present in the political conversation may be sufficiently ecologically invalid as to render the conclusions moot.

Similar complications await those hoping to use surveys to unravel the information processing mechanisms underlying attitude formation. Take, for example, the goal of estimating how ten different informational beliefs collectively shape individuals' attitudes toward a presidential candidate, where these ten beliefs themselves vary across five different dimensions (e.g., certainty, intensity, importance, etc.). Before accounting for the likely interactions between different features of beliefs, we would be estimating 50 distinct parameters, and the number of regression coefficients would increase exponentially if we were to allow interactions between dimensions or consider other dimensions of the beliefs. With most survey samples, an ordinary least squares regression analysis with maximum likelihood estimation could hardly make reasonable estimates of these parameters without confronting the problem of overfitting (Harrell, 2001). Adding to this challenge, different beliefs about the same attitude object are often closely related to one another and are collectively shaped by factors like ideology, class, partisanship, or racialization (Bolsen et al., 2014; Jeffres, 2000; Judd & Krosnick, 1989). The regression models attempting to plumb the simultaneous influences of different beliefs would thus often fall apart due to multicollinearity and other estimation biases (Rosenthal, 2013). Here too, methodological challenges have rendered opaque the links between individual pieces of information and the overall attitude. Perhaps unsurprisingly, the academic efforts to investigate how these complex attitudes are formed have been fraught, as too have real-world attempts to influence these attitudes (Eagly & Chaiken, 1995).

Can a Bayesian model identify Bayesian updating?

This dissertation proposes a new model to examine how a multitude of informational beliefs relate to individuals' expressed attitudes, which provides a better understanding of the psychological mechanism of information processing underlying the formation of political attitudes toward a complex object. At its core, the model builds on the notion that different informational beliefs about various attributes or components of an attitude object will have structurally similar relations with the overall attitude. It then leverages Bayesian statistics with Markov Chain Monte Carlo (MCMC) algorithms to estimate parameters for the links between different informational components and the overall attitude in a more efficient, less presumptive, and more scalable manner (Gelman et al., 2013; Gill, 2008; Jackman, 2000a, 2000b).

In fact, scholars have long believed that people's attitude formation and attitude change might reflect a Bayesian way of thinking, which essentially means revising estimations or expectations based on new information or evidence (e.g., Anderson, 1990; Charter & Oaksford, 2008; Fishbein & Azjen, 1975; McGuire, 1960). In everyday life, Bayesian updating often occurs in an intuitive and informal manner. People tend to weigh new information against their existing beliefs and adjust their attitudes accordingly based on the perceived credibility and relevance of the new evidence. This process of belief revision shares many similarities with the core principles of Bayesian updating, even if people do not consciously apply Bayes' theorem in its mathematical form. Interestingly, no prior studies, to the best of my knowledge, have used Bayesian methods to examine whether the formation of political attitudes is really based on the mechanism of Bayesian updating. The current project serves as the first of its kind to empirically explore this uncharted territory.

Bayesian methods have two comparative advantages to address the challenges facing traditional methods. First, it allows the incorporation of a prior probability distribution when making inferences and estimations. The prior can be informed by previous research, pre-existing evidence, expert opinion, or reasonable and justifiable assumptions. In practice, this feature of Bayesian methods could allow us to impose a matrix structure regulating the relationships between different information dimensions and the overall attitude across different beliefs, which helps circumvent the problem of multicollinearity and can collectively consider the impact of a constellation of related beliefs.

Second, different from the traditional frequentist approach, Bayesian methods estimate parameters in a completely different way. Essentially, this approach considers every parameter as a random effect instead of a fixed effect and estimates the posterior probability distribution of the parameter through intensive computation. Bayesian methods thus have the capability to estimate a large number of parameters simultaneously without hitting the problem of overfitting.

With these two features, Bayesian methods could build a model to systematically and comprehensively investigate the information processing mechanism underlying political attitude formation. In practice, this model allows us to ask: When people form attitudes toward a complex object, to what extent are different pieces of information about the attitude object being leveraged? What are the psychological mechanisms whereby different informational beliefs about an attitude object shape the ultimate attitude? And if the overall attitude is at least in part a product of the informational beliefs about different attributes or components of the object, the model will allow us to estimate what people's attitudes would realistically look like if they were better-informed through simulating different counterfactual scenarios. The current project proposes to answer these questions in the context of a highly complex, contentious, and consequential public policy—the Patient Protection and Affordable Care Act, or, as it is colloquially known, Obamacare.

The Affordable Care Act

The Affordable Care Act (ACA) is an ideal context for understanding how informational beliefs—both accurate and inaccurate—might collectively shape an individual's overall attitude toward a complex attitude object. The legislation was passed by the U.S. Congress and signed into law by President Barack Obama in 2010. The ACA enacted a series of fundamental changes to the U.S. health care system through amending the U.S. Code to prevent insurance companies from denying coverage for pre-existing conditions, provide for health care exchanges where individuals could purchase care directly, require all individuals to have health insurance or pay a fine, and more, which elicited an extremely partisan reaction and considerable public attention and news media interest.

The ACA represents a good case study for the information processing mechanism underlying political attitude formation both because Americans appear to hold real attitudes about the legislation and because those attitudes—if people are indeed acting as Bayesian updaters—should ideally be based on the combination of evaluations of a complex-yet-bounded set of constituent parts. Moreover, these attitudes have proven consequential not just for evaluations of the law itself, but also as a basis for widespread election messaging.

First, unlike many other legislations and public policies that are processed under the radar with little media coverage and few polls documenting public opinion, the ACA is arguably one of the most high-profile pieces of legislation in the U.S. for decades, with an enormous amount of (both correct and incorrect) information circulating in the public sphere, some of which are so famous or notorious (e.g., the "individual mandate" or the so-called "death panel") that they are very likely known to and could potentially be leveraged by the public when they form and express their attitudes toward the law.

Second, the ACA is really the sum of a complex combination of constituent parts. As Lupia (2016) noted, the law is 906 pages long with numerous technical terminologies. Even the table of contents alone spans 12 pages. The ongoing public debate and litigations challenging the constitutionality of the law further add new (correct and incorrect) information as well as confusion about the status of the law. Whereas the complexity of the law makes it almost impossible for anybody to claim that they fully understand every detail about the law, it offers a unique opportunity to examine whether individuals' attitudes toward a complex object are derived from their beliefs of and evaluations of different components of the object based on the information about those components.

Third, the public opinion surrounding the ACA seemed to be so volatile yet so consequential that it may have shaped the outcome of two elections. In 2010 when the ACA bill was passed and signed into law, negative attitudes toward it largely outweighed positive views, which was purported to deliver Republicans a landslide victory in the midterm election that year (Bedard, 2011; Kliff, 2012; Nyhan et al., 2012). In 2018, in contrast, opposition to the Trump administration's attempt to repeal the ACA became major leverage for Democrats that many political pundits and scholars argue cost Republicans the U.S. House (Bussing et al., 2022; Pramuk, 2019; Scott, 2018). To what extent these claims are accurate remains open to debate and further scrutiny. However, it cannot be denied that a vast number of political messages from both sides of the spectrum have concentrated on this legislation, and public opinion on the ACA has profoundly influenced American politics for over a decade (Lavanty, 2018; Pacheco et al., 2020). As a result, investigating the processes that shape public attitudes towards the law holds both scholarly and societal importance.

In fact, a popular narrative about the ACA in scholarly and media discourse might shed light on why the law is particularly suitable for examining how information might (or might not) influence the formation of political attitudes—that people liked what was in the law even while they opposed the law itself (Brodie et al., 2010; Deane et al, 2011). Through various opinion polls over a decade, the American public regularly reported positive attitudes towards most key components of the law ranging from providing discounts on prescriptions to seniors with high drug costs to preventing insurance companies from denying coverage for pre-existing conditions.

Yet attitudes toward the law overall were at best described as equivocal, if not slightly net negative (Gallup, 2020; Kaiser Family Foundation [KFF], 2023; Pew Research Center [Pew], 2017).

Implicit in the claim that individuals liked most provisions of the ACA but opposed the law itself are two possibilities: First, people's attitude toward a complex public policy might not necessarily be a function of beliefs on and evaluations of various components of the policy. Presumably, we would expect that an ideal version of the attitude formation process occurs with individuals learning about the components of a policy, evaluating those components, and aggregating those evaluations to render a summary judgment. In reality, however, there might be other factors influencing how individuals make their judgments. In the case of the ACA, for example, the opposition to the law might be derived from the awareness of the fact that the law was overwhelmingly supported by Democrats and opposed by Republicans, and Republican-identifying individuals might oppose the law as a way to signal their identity, rather than as a consequence of evaluations of different provisions of the law based on the information they have. If this is the case, providing accurate information with the aim of increasing correct beliefs and consequently changing public attitudes is destined to fail because information is simply not the source of attitudes.

Second, it remains possible that information still plays an important role in shaping individuals' attitudes toward a complex public policy, but people simply did not have the information they needed. That is, ignorance due to a lack of information and/or erroneous beliefs due to disinformation and misinformation might outweigh knowledge and correct beliefs in people's attitude formation process. In the case of the ACA, for example, people might welcome the idea of allowing children under 26 to be covered by their parents' health insurance plans but they do not know that this clause is indeed a part of the law, and they might genuinely believe that the so-called "death panel" (i.e., a plan to institute a panel of bureaucrats that could decide whether people get medical care) is real, and such ignorance and misperceptions might contribute to a more negative attitude toward the policy. Only if this is the case would strategies of public education and correcting dis/misinformation not become meaningless endeavors, and we would expect that, *ceteris paribus*, a better-informed public would hold a different (and presumably a more favorable) attitude toward the law.

A more apparent yet troubling reality about the public attitudes toward the ACA is the enormous and persistent partisan divide over the issue. Even in this era of unprecedented political polarization, the ACA still "stands out as one of the most politically divisive pieces of legislation in recent history" (Brodie et al., 2019, p. 423). Numerous opinion polls have been documenting the partisan divide over the issue for more than a decade (Fingerhut, 2017; Jones, 2020; KFF, 2023). In fact, research has shown that the law was getting more popular while the partisan division over the law was also becoming greater (Brodie et al., 2020)

So why do individuals with different partisan affiliations come to such divergent views of the ACA? There are at least three likely explanations. First, individuals in different partisan groups could have been exposed to different pieces of information and therefore hold different beliefs about what the ACA would do. In fact, past research has shown that beliefs about the ACA—both correct and incorrect—are distributed unequally across partisan lines. For example, Republicans are just more likely to believe that the law will actually create a "death panel" than Democrats (Meirick, 2013; Nyhan, 2010). Therefore, partisans might just have diverging bases of information (and dis/misinformation) about the ACA that collectively led different partisan groups to assess the law differently. Second, individuals of different partisan groups might have evaluated aspects of the law differently because of their pre-existing values and ideologies. That is, even for something that they all believe the law will do, they could have differed in whether they see that expected outcome as good or bad, desirable or despicable. For example, Democrats might genuinely like the idea of providing discounts on prescriptions to seniors with high drug costs more than Republicans, as the value reflected in that provision is more enshrined in their ideology. Finally, individuals' attitudes toward the law may have been expressive in nature (c.f., Bullock et al., 2015; Prior et al., 2015). To this end, they may have evaluated the law based on which party was supporting it while ignoring the content of the law in their judgments. Most likely, all of these are to some extent true. In any case, understanding the formation of public attitudes toward the ACA requires a model estimating how different beliefs about the law, evaluations of different components of the law, and partisan identities collectively shape people's overall attitudes toward the law.

The current project

This dissertation proceeds as follows: Chapter 2 outlines the theoretical framework for the project. It introduces the normative model whereby informational beliefs about different attributes of the attitude object are expected to shape the overall attitude toward the object (Fishbein, 1963; Fishbein & Ajzen, 1975), and considers how different dimensions of beliefs might influence the process of attitude formation. It also discusses how attitudes might be developed from other processes such as identity signaling.

Chapter 3 offers a brief introduction to Bayesian statistics, explains how an informative prior is incorporated into the estimation process and how the computation of posterior probability distribution of parameters is conducted, and discusses why it is the appropriate approach to address existing challenges facing current methods.

Chapter 4 details the data that will be used in the current project, describes how the core concepts were operationalized, and presents detailed descriptive analyses for all major variables, in particular the distributions of beliefs about and evaluations of different provisions of the ACA, as well as the overall attitude toward the ACA, across different partisan groups.

Chapter 5 tests the applicability of the normative model of information synthesizing in political attitude formation. Leveraging Bayesian methods, it evaluates how a variety of informational beliefs regarding different components of the ACA as well as different dimensions of those beliefs collectively shape the overall attitude toward the ACA. It also considers the potential impact of partisan identities and investigates whether individuals of different partisan groups demonstrate a similar pattern in the information processing mechanism underlying their political attitude formation.

Building on the Bayesian model which allows considering the impacts of changing constellations of beliefs collectively and simultaneously, Chapter 6 estimates what people's attitudes toward the ACA might look like if they were better-informed. By simulating different counterfactual scenarios where people hold perfectly accurate information and are fully certain in the information that they possess, it demonstrates the possible effects that information could realistically have on swaying individuals' political attitudes. It also reveals to what extent the attitudinal gap between partisan groups could be attributed to differences in beliefs about what constitutes the law, to differences in evaluations of the components of the law, and to inherent partisan divisions.

Lastly, Chapter 7 discusses the theoretical and methodological contributions of the dissertation. It highlights how Bayesian methods facilitate a comprehensive examination of a belief-based attitude model, addresses the importance of considering a counterfactual public and how it might inform policy discussions for real-world politics, and concludes the project.

CHAPTER 2

An Ideal Model of Political Attitude Formation

Expectancy-value model of attitude: A belief-based model

Overview

How do people form their attitudes toward a complex object such as a decision of the Supreme Court, a spending bill passed by Congress, or even a presidential candidate? Despite their many disagreements on definitions, measurements, or principles of calculations, it seems that most researchers tend to agree that the formation of attitudes reflects a course of information processing (e.g., Anderson, 1959, 1962; Bettman et al., 1975; Edward, 1990; Fishbein, 1963; Fishbein & Azjen, 1975; McGuire, 1960b, 1969). Ideally, we would expect that people first gather information about different components of the attitude object, evaluate those components based on the information they have, integrate those evaluations in accordance with their respective importance or relevance, and eventually render a summary judgment.

This process is articulated by the expectancy-value model of attitude (Fishbein, 1963, 1967; Fishbein & Azjen, 1975, 2010). As Fishbein and Azjen (2010) put it, "[H]uman social behavior follows reasonably and often spontaneously from the information or belief people possess about the behavior under consideration" (p. 20). Specifically, an individual's attitude toward an object is posited to be derived from her or his beliefs that the object has certain attributes (i.e., expectancy) and the evaluations of those attributes (i.e., value). The beliefs and the attribute evaluations will then produce the overall attitude toward the object in a summation manner:

$$Attitude \propto \sum_{i=1} b_i e_i$$

where b_i is the belief that the attitude object has attribute i, and e_i is the evaluation of attribute i. In other words, the overall attitude toward an object should be proportional to the sum of the products of the cognitive beliefs that an object has certain attributes and the affective evaluations of each of those attributes (Ajzen, 1991; Fishbein & Azjen, 1975).

To provide the following discussions with a clear and solid ground, the three foundational concepts in this model must be defined. In general, an attitude can be understood as an evaluative orientation (Krosnick & Smith, 1994). More specifically, an attitude is defined as "a learned predisposition to respond in a consistently favorable or unfavorable manner with respect to a given object" (Fishbein & Azjen, 1975, p. 6), which represents an overall evaluative judgment about the attitude object.

Belief represents a piece of information about the attitude object that the individual considers to be true. Specifically, a belief links an object to an attribute. Based on either direct observation or inference or information received from outside sources, an individual could form a number of beliefs about an object. That is, she or he could associate that object with multiple distinct attributes (Fishbein & Azjen, 1975). The totality of an individual's beliefs about the attitude object, therefore, serves as the informational foundation from which that individual is expected to form her or his overall attitude toward the object. In contrast, when individuals do not believe that a particular attribute describes an object, even if there is a real association between the two, their evaluations of the attribute are presumed to be inconsequential to their overall attitudes. The terms belief and information are sometimes used interchangeably in this dissertation, but of course, a piece of information can only become a belief when the individual chooses to lend it some degree of credibility.

Each of those attributes that an individual associates with the attitude object might also be evaluated favorably or unfavorably based on the associations between that attribute and other traits or qualities. That is, these attribute evaluations are themselves attitudes and a function of beliefs linking the attribute to other characteristics and evaluations of those characteristics, and these evaluations are again based on beliefs and evaluations. Although it is theoretically possible to continue such an analysis indefinitely and trace through the development of an individual's attitudes back to the beginning of her or his life to account for the initial acquisition of affect (Hess & Torney, 1967), the usual practice is to assess the evaluations of the attributes associated with the attitude object at a given point of time (Edwards, 1990). For the purpose of the current study, the term *evaluation* is exclusively used to refer to a *specific* judgment with regard to any *individual* attributes or components of the overarching attitude object.

Few prior scholars have directly applied the expectancy-value model of attitude in political communication and public opinion research (but see Chong & Druckman, 2012). Nevertheless, the idea embedded in this model is implicit in many studies. For example, in his seminal works on the nature and origins of public opinion, Zaller (1992) draws a vivid analogy that "[e]very opinion is a marriage of information and predisposition: information to form a mental picture of the given issue, and predisposition to motivate some conclusion about it" (p. 6), which to a great extent corresponds with the notions of beliefs and evaluations. Zaller (1992) regards considerations as the building blocks of public opinion, because any individual's expressed attitude, according to his Receive-Accept-Sample (RAS) model, reflects the process of sampling the most salient considerations available in the person's mind. The consideration, however, consists of a cognitive component and an affective component, which respectively refer to "a belief concerning an object and an evaluation of the belief" (Zaller, 1992, p. 40). Therefore, even without explicitly referring to the expectancy-value model of attitude, Zaller's (1992) work, as well as the studies built upon his tradition, which arguably constitutes the mainstream of contemporary public opinion research, actually assumed or even internalized the expectancy-value model of attitude. And as will be shown in the following analysis, it is indeed crucially important to decompose considerations into beliefs and evaluations, in order to better understand the formation of political attitudes.

Belief

The first element to be considered in the expectancy-value model of attitude is belief. Specifically, a belief is a piece of information asserting that an attitude object possesses a particular attribute (Fishbein & Azjen, 1975). People's beliefs about an object could be formed in a variety of ways—they may be learned through direct experience or observation, they could be obtained through making inferences, or, perhaps most commonly in the context of public affairs and politics, they could be acquired through receiving and accepting messages from external sources such as family, friends, traditional media, and social media (Anspach, 2017; Bowler et al., 1993; Chaffee & Kanihan, 1997; Johnson et al., 1999; Westerman et al., 2014).

It is important to note that individuals from different social backgrounds and/or with different personality traits could drastically differ in both their personal experiences and the sources of information to which they are exposed, as well as also how they remember, process, and interpret information (Garrett; 2009; Knobloch-Westerwick & Meng, 2009; Matthews, 2008; Sears & Freedman, 1967; Stroud, 2008, 2010). Therefore, their beliefs about the same attitude object might be, and in many cases are, very different (Alesina et al., 2020; Dolan, 2011; Potter, 1986). Moreover, the beliefs that individuals hold are not necessarily veridical. In fact, they are often inaccurate, biased, self-serving, and irrational (Ajzen, 2020; Sperber, 1982). However, once a set of beliefs is formed, it provides the cognitive foundation from which attitudes are assumed to follow in a consistent and often spontaneous way (Fishbein & Ajzen, 2010; Wyer & Albarracín, 2005).

In the context of a complex attitude object such as a public policy with intricate details, people might develop differing beliefs about what a policy actually encompasses—some individuals might be very well-informed and possess accurate beliefs about major provisions of the policy; some individuals might be misinformed and hold erroneous beliefs about the composition of the policy, probably due to exposure to dis/misinformation. Regardless of the accuracy of their beliefs, the expectancy-value model of attitude contends that each individual's overall attitude toward a policy should be shaped by what they believe comprises the policy. In more general terms, public support for or opposition to a policy is presumably a function of what people believe that the policy will or will not do.

Evaluation

The evaluation of an attribute refers to one's subjective assessment of the favorability of an attribute of the attitude object, which is itself an attitude and is based on whether the value associated with or the outcome expected from that attribute is deemed desirable or undesirable (Fishbein & Ajzen, 2010). People come from different backgrounds with different values, interests, goals, and life experiences, among other things (Albarracin & Shavitt, 2018; Zaller, 1992). All these differences could contribute to different evaluations of different attributes of an object.

It is surely beyond the scope of this dissertation to explore and identify the sources of variability in people's attribute evaluations. That is, this project will not investigate why a certain component of the attitude object is evaluated more positively than the others or why a certain attribute of the attitude object is found favorable among some individuals but not among other people. However, it is clear that the evaluation of an attribute regulates how the belief about the corresponding attribute shapes the overall attitude, as the expectancy-value model of attitude indicates (Fishbein & Ajzen, 1975). And as will be discussed in the following analysis, attribute evaluation plays an essential role in helping identify the relative importance of a belief, which is crucial to the model that this dissertation will propose.

At the same time, it is also important to note that this project assumes an effect of attribute evaluation independent of the belief about the corresponding attribute. That is, the attribute evaluation could affect the overall attitude even if the attribute being evaluated is not believed to be a part of the attitude object. Counter-intuitive as it might sound, it is indeed perfectly sensical and will contribute to our understanding of the relationship between beliefs and attitudes.

Empirical support for a belief-based attitude model

As previously noted, few political communication and public opinion studies have directly tested the expectancy-value model of attitude. However, a variety of projects, in particular those demonstrating the effectiveness of dis/misinformation correction and public education, could be considered lending support to the general idea of a belief-based attitude model, as the only plausible explanation for the attitudinal changes ensued from the endeavors of providing accurate information seems to be that these updated beliefs brought by the new information are leveraged by individuals in their attitude formation process.

For instance, Thorson's (2016) work on the effects of correcting misinformation on candidate evaluation provided empirical evidence that informational beliefs are antecedents of attitudes. In two experiments, participants with exposure to both misinformation and correction reported a more negative attitude toward the candidate compared to those who were never exposed to the misinformation, but a more positive attitude compared to those who only saw the misinformation but not the correction, which suggests that the correction of misinformation leads to an update in beliefs and subsequently changes in attitudes.

Bode and Vraga's work (2015) shows similar evidence. In two experiments, participants' attitudes toward genetically modified organisms (GMOs) and vaccines turn more positive after exposure to information correcting the misperception of GMOs causing illness and the information debunking the vaccine-autism link respectively. In fact, Chan et al.'s (2017) meta-analysis of 52 studies shows that debunking misinformation has large effects (*d*s = 1.14–1.33) on changing people's attitudes.

Research on deliberative democracy also provides insights into the impact of informational beliefs on attitudes. For example, Zhang (2018) argues that the presence of new arguments and perspectives different from one's own predispositions is key to the revision of policy preferences. Across a variety of issues from state legislature transparency to government accountability, Zhang (2018) shows that exposure to more dissimilar views is associated with greater changes in stated opinions, presumably because exposure to new information and updates in beliefs bring about changes in attitudes.

Other scholars leveraged statistical simulation techniques to test the effects of informational beliefs on attitude. For instance, Bartels's (2005) work on the Bush-era tax cuts suggests that if working-class individuals had been well-informed about the policy, they would have realized that it was against their interest, and they would have ultimately decided to oppose the cuts. The changes in informational beliefs lead to corresponding changes in attitudes. All in all, these studies demonstrated that a belief-driven attitude model on the basis of information appears to be warranted.

All beliefs are equal but some are more equal than others

It is worth noting that the expectancy-value model of attitude, while built on the basis of beliefs, does not suggest that all beliefs about an attitude object will be leveraged during the process of attitude formation. On the contrary, only a small number of beliefs will determine the attitude at any given moment due to human beings' limited capability to attend to and process information (Lang, 2000; Miller, 1956). Fishbein and Azjen (1975, 2010) argued that only salient or easily accessible beliefs would serve as the prevailing determinants of attitude and that a set of modal salient beliefs should be solicited in empirical studies to examine the influences of beliefs in the attitude formation process. A similar mechanism was articulated in Zaller's (1992) RAS model that an individual's expressed attitude was formed through the process of sampling the most salient considerations available in his or her mind at the time of making opinion statements.

In terms of political attitudes and public opinion, the single most important source of information is unquestionably news media, which was, at least prior to the emergence and prosperity of social media platforms, dominated by elite discourse (Zaller, 1992), and many scholars would contend, still remains elite-dominated (e.g., Harder et al., 2017; Kennedy & Moss, 2015; McGregor, 2019; Wetts, 2020). Therefore, from the perspective of political communication and public opinion research, beliefs about the attitude object might be best identified from political debates and media narratives, which is where the beliefs to be analyzed in this project were drawn from (KFF, 2012).

However, among the selected set of modal salient beliefs, the original expectancy-value model of attitude did not thoroughly investigate the mechanisms by which some beliefs might matter more than others in terms of how they shape the ultimate attitude. The impact of different beliefs on the overall attitude might vary because of differences existing in the nature of those beliefs. This dissertation proposes two features where the beliefs differ and might further contribute differing influences on the ultimate attitude to be considered, namely belief certainty and belief importance.

Belief certainty

As noted before, individuals might hold vastly different beliefs about the same attitude object because of distinct personal experiences, information sources, etc. At the same time, individuals might also vary in the certainty with which they hold particular beliefs. In information theory, the degree to which a message is informative could be understood as the amount of uncertainty it reduces (Shannon & Weaver, 1949). Certainty is therefore a result of the amount, clarity or ambiguity, and consistency of the information available to an individual (Gross et al., 1995).

In the context of public opinion and political attitudes, some individuals might be highly attentive to current affairs and are very well-informed politically. They therefore possess not only accurate beliefs but also a high level of certainty in the beliefs they hold. Other individuals, likely the vast majority of the public, generally pay little attention to politics and public affairs. Whereas they may also have a vague idea about a political figure or a public policy, either through hearing from a friend during chit-chat or reading from a post while scrolling through Facebook, they simply do not know it for sure. For example, an average citizen and a "news junkie" might both know that President Joe Biden visited Kyiv during the ongoing Russian invasion of Ukraine. However, the degree to which they feel certain about that piece of information could vary a great deal. And if we were to assess how President Biden's support for Ukraine influences his overall approval rating, the same belief that he had visited Ukraine might not have the same effect on these two persons even though they have the same level of support for the visit, because a belief held with less certainty is likely to be discounted.

Little prior research has empirically examined the role of belief certainty in the process whereby multiple informational beliefs might collectively shape overall attitudes. However, research on attitude certainty in the attitude strength literature might help shed light on the discussion on belief certainty. Defined as "a subjective sense of conviction or validity about one's attitude" (Gross et al., 1995, p. 215), attitude certainty has been found positively correlated with attitude extremity and polarization (Krosnick et al., 1993; Pelham, 1991). Attitudes held with greater certainty are less susceptible to the impact of contextual factors and are more persistent over time than attitudes held with less certainty (Bassili, 1996; Bizer et al., 2006; Schwarz & Bohner, 2001). Attitude certainty also contributes to attitude-behavior correspondence such that attitudes held with greater certainty are more predictive of behavior (Rucker & Petty, 2004; Tormala & Petty, 2002).

One notable study from the attitude strength literature that is particularly relevant to the current project is Peterson's (2004) work on attitude certainty and political candidate evaluation. Even though "framed" as research on attitude certainty, the certainty that Peterson (2004) explored was actually more closely associated with the concept of belief as defined in the current project, because the certainty measure was assessing how sure people were about two fictitious candidates' stands on a variety of policy issues. According to the definitions of attitudes and beliefs in the expectancy-value model of attitudes (Fishbein & Azjen, 1975), an individual's understanding of a political candidate's stand on any given policy should reflect a piece of information linking the attitude object (i.e., the candidate) to an attribute (i.e., policy stand), which therefore constitutes a belief that is informational in nature, rather than an attitude that is an evaluative orientation in nature (Krosnick & Smith, 1994). Peterson (2004) found that the impact of voters' policy preferences on their overall attitudes toward the candidates depends on their certainty about the candidates' stands on those policy issues. For the participants who are most uncertain about the policy positions of the candidates, their evaluations of individual policies do not seem to influence their overall attitudes toward the candidates.

Drawing from the literature on attitude strength, the present study posits that beliefs held with greater certainty are more likely to be used in the attitude formation process. Conversely, beliefs accompanied by a low degree of certainty are less likely to be incorporated into this process. When individuals are confident in their belief about a particular attribute of the attitude object, that belief is likely to weigh more heavily on the summary judgment that they make about the object. On the contrary, uncertainly held beliefs should have less of an effect on attitude formation. Collectively, then, the overall attitude is more likely to be derived from the beliefs held with greater certainty than those held with less certainty. The certainty of beliefs, therefore, plays a regulatory role in the process of attitude formation.

In fairness, the original expectancy-value model of attitude did not consider belief certainty as a separate factor that might moderate the impact of belief probably because the idea of belief certainty was largely internalized in the measure of belief. The model was primarily used in studying behaviors and since the attitude object is a behavior, belief is defined as the subjective probability judgment concerning the occurrence or consequence of a behavior, which itself implicitly captured the idea of certainty. The concept of belief is usually measured by a question like “How likely do you believe this behavior will generate a particular outcome?” Someone who answers “extremely likely” thus has greater strength in her or his belief than someone who answers “slightly likely.” Such difference, however, could also be understood as varying degrees of belief certainties, as the likelihood estimation, at least to a certain extent, reflected the individual’s confidence or conviction in that belief. In fact, Fishbein and Azjen (1975) had sometimes equated belief strength with belief certainty by indicating that some beliefs were initially high in strength because they were “held with maximal certainty” (p. 132) and that the strength of some beliefs based on little information was low because “[The] subjective probability may be at chance level, indicating a high degree of uncertainty” (p. 134).

However, when the attitude object is not a behavior but a substantive matter, as, for example, a public policy in the current project, it is simply nonsensical to ask people to estimate the likelihood that an established policy contains a certain provision. The belief needs to be measured in a dichotomous way that individuals either believe or do not believe that a certain provision is part of the policy, which cannot capture the idea of certainty in an implicit manner. Therefore, the question about belief certainty needs to be asked explicitly and constitutes a separate variable to be considered and analyzed in the model.

It is once again worth noting that the potential impact of belief certainty is not conditional on the accuracy of beliefs. In the context of a complex public policy where some of the information widely circulated about the policy might be substantively inaccurate, individuals might also have great certainty in the incorrect beliefs they hold about the policy. The certainty associated with these beliefs too should influence their ultimate attitudes toward the policy.

The potential effect of belief certainty irrespective of belief accuracy actually highlights a collateral benefit of separately gauging people’s certainty of their beliefs. Kuklinski and colleagues (2000, 2001) have shown that information has not one but two dimensions—quantity and quality. Those individuals who hold no beliefs about a policy with any certainty can be considered uninformed, i.e., low in both quantity and quality. Those who hold a large number of correct beliefs with great certainty can be considered knowledgeable, i.e., high in both quantity and quality. Importantly though, some people may possess a multitude of incorrect beliefs which they hold with a high degree of certainty. This group can be best considered misinformed, i.e., high in quantity but low in quality.

This tripartite distinction has become increasingly relevant in recent years. News media has long been the major source of information on public affairs and politics with a strong influence over the public's policy attitudes (Iyengar & Kinder 1987; Zaller 1992), and it had been able to, generally speaking, provide the public with objective, impartial, and accurate information, as how journalistic professionalism commands (Allan, 1997; Beam, 1990; Schudson, 2001). Therefore, in the pre-Internet era, researchers' major concern about the public in terms of their informedness was primarily the distinction between the uninformed and the knowledgeable (Delli Carpini & Keeter, 1996; Prior, 2007). However, with the increasing prevalence of partisan media sources and social media news provision, a growing share of factual information has been replaced—or at least supplemented—with partisan propaganda, biased opinions, and "fake news" (Egelhofer & Lecheler, 2019; Vargo et al., 2018). Therefore, the distinction between those who are uninformed and those who are misinformed may now be more important than in the past (Li & Wagner, 2020; Pasek et al., 2015), and the influences of ignorance (i.e., lack of correct beliefs) and misperception (i.e., certainly held incorrect beliefs) on people's political attitudes could potentially be very different (Li & Pasek, 2022; Kuklinski et al., 2000).

Belief importance

The other feature where beliefs might vary and further contribute differing influences on the formation of attitudes is the importance attached to beliefs (Higgins, 1996; Olson et al., 1996). Even for the modal salient beliefs that individuals hold with the same level of certainty, it would be nonsensical to assume that people would simply sum all these beliefs about an attitude object indiscriminately in service of a final attitude. Some attributes of an attitude object are consequential whereas others are of little relevance, and what attributes are of greater importance than others might also vary across different groups or individuals. For example, in reviewing the public opinion data of three U.S. presidential elections, Krosnick (1988) found that policy issues deemed as more important tended to have a greater impact when estimating the influences of individuals' preferences for different policies on their overall attitude toward presidential candidates. Similarly, Liu et al. (2020) reported that issue advocacy could increase individuals' perceived importance of beliefs, and beliefs with growing importance contributed a greater impact on the ultimate issue attitude. Hence, due to differences in the importance of different attributes, the beliefs about different attributes should not merit equal consideration by individuals in the formation of attitudes (Boninger et al, 1995). They should be weighted differently.

Unlike belief certainty discussed previously, the notion of belief importance has actually received extensive examination in studies on the expectancy-value model of attitude. For example, van der Pligt and de Vries (1998a) tested the relationships between 15 different beliefs and respondents' attitudes toward smoking, and found that the summed score of the three most important beliefs as identified by the respondents and their overall attitude had a correlation coefficient of .64; whereas for the remaining 12 less important beliefs, the coefficient of correlation between their summed score and the overall attitude was merely .15. The differences in correlations between beliefs with varying degrees of importance and overall attitudes have been examined and supported by several other studies (e.g., Budd, 1986; van der Pligt & de Vries, 1998b; van Harreveld et al., 2000). It thus seems apparent that beliefs with greater importance should be weighted more, and belief importance should be added as a third multiplicative variable in addition to beliefs and attribute evaluations to the original model, as demonstrated in the following equation:

$$Attitude \propto \sum_{i=1} b_i e_i \omega_i$$

where b_i is the belief that the attitude object has attribute i, e_i is the evaluation of attribute i, and ω_i is the importance (weight) attached to attribute i.

This addition, however, was deemed redundant and unnecessary by the architects of the expectancy-value model of attitude. Fishbein and Azjen (2010) argue that despite the closer correlation between the more important beliefs and the overall attitude, adding belief importance as a third multiplicative variable to the model has little discernible effect on the prediction of attitude, because the variance that is supposed to be captured by belief importance has already been absorbed by beliefs and attribute evaluations. That is, beliefs considered to be more important by any individual are also typically evaluated more positively or negatively (i.e., with greater magnitude or extremity in attribute evaluations) than beliefs deemed less important by the same individual. Similarly, people usually have more information about issues that are more important to them; therefore, the fact that some beliefs are held more strongly (or with greater certainty as discussed in the previous section) might have already reflected that these beliefs are more important. As a result, belief and attribute evaluation measures "may capture enough of subjective importance to make redundant any independent assessment of belief importance"

(Fishbein & Azjen, 2010, p. 111). In an empirical test of this proposition, Kenski and Fishbein (2005) examined eight different beliefs in the context of the 2000 U.S. presidential election and found that the perceived importance of beliefs is highly correlated with the extremity of evaluations of those beliefs.[1]

In the context of public policy attitudes, there might be different manifestations of a policy being perceived as more important. Take, the Economic Impact Payments (EIP) during the COVID-19 pandemic, or the "stimulus checks" as it is colloquially known, for example. Some individuals (e.g., people who lost their jobs during the pandemic) might evaluate this policy extremely positively, which could be indicating both their favorability of the policy and the fact that it is really important to them. Attribute evaluation, therefore, partly captures the idea of belief importance. Some other individuals (e.g., a libertarian economist who studies social welfare policy) might not be particularly enthusiastic about this idea because of their pre-existing values but know this policy very well with great certainty because of their jobs or interests. In this case, belief and belief certainty might have captured the idea of belief importance.

The current project, therefore, recognizes the possibility that the variance in belief importance might have already been captured by belief and attribute evaluation (Fishbein & Azjen, 2010; Kenski & Fishbein, 2005), as well as belief certainty. However, a different method should be adopted to approach this problem, because, conceptually speaking, the variance in belief importance being captured by other variables due to measurement issues does not disqualify belief importance from making its unique contribution to the attitude formation process. The current project argues that belief importance could be considered as a latent construct that is jointly captured by belief, belief certainty, and attribution evaluation, and should

[1] This, of course, may be more reflective of empirical multicollinearity than theoretical overlap.

be empirically examined in the expectancy-value model of attitude. For each attribute i of the attitude object, its importance ω_i could be jointly assessed by three observed variables—belief (B_i), the certainty associated with that belief (C_i), and the evaluation of the corresponding attribute (E_i).

A revised expectancy-value model of attitude

This project, therefore, proposes a model to test the process by which (both accurate and inaccurate) beliefs about different attributes of an object collectively shape the overall attitude toward that object. In general, this model proposes that an individual's overall attitude toward any given object should be a function of (1) what the individual believes to be an attribute of the object, (2) the degree to which the individual is certain that the object has that attribute, and (3) the individual's evaluation of that attribute, all of which weighted by (4) the relative importance of that attribute. The conceptual model is presented in the following equation:

$$Attitude \propto \sum_{i=1} (bce)\omega_i$$

where b represents belief, c represents belief certainty, e represents attribute evaluation, and w_i represents the relative importance of attribute i.

Different from the original expectancy-value model of attitude, this revised model posits that belief, belief certainty, and attribute evaluation should have structurally similar relations with the overall attitude across different attributes of the attitude object. For instance, if favoring one attribute of an object has a positive relation with favoring the overall object, we expect to observe a similar relation for all other attributes as well. And for each individual attribute i of the attitude object, the unique effects of its corresponding belief, belief certainty, and attribute evaluation on the overall attitude are actually determined by this overall pattern weighted by the relative importance of attribute i.

In other words, if we have accounted for these components of an attribute—what the belief is, how certain that belief is held, and what the evaluation of that attribute is—then the remaining relevant component would be how much of a weight these components all have, which presumably is the only thing that would vary depending on the particular attribute of interest.

This might be more clearly explained with an example where we have an attitude object O with three distinctive attributes. The belief, belief certainty, and attribute evaluation associated with each individual attribute were directly measured, as illustrated in the following table:

Table 2.1 *Summary of Conceptual Variables Related to the Overall Attitude*

Attribute / Variable	Attribute 1	Attribute 2	Attribute 3
Belief (B)	B_1	B_2	B_3
Belief certainty (C)	C_1	C_2	C_3
Attribute evaluation (E)	E_1	E_2	E_3

In theory, however, the effect of belief about Attribute 1 on the overall attitude (b_1) should be understood as the uniform influence of belief on the overall attitude across different attributes (b) weighted by the relative importance of Attribute 1 (ω_1), and the same applies to the effects of beliefs (b_i), certainties of beliefs (c_i), and evaluations for all attributes (e_i), as demonstrated in the following table:

Table 2.2 *Summary of the Effects of Conceptual Variables Related to the Overall Attitude*

Attribute importance / Effect of variable	Attribute 1 Importance (ω_1)	Attribute 2 Importance (ω_2)	Attribute 3 Importance (ω_3)
Belief (b)	$b_1 = b\omega_1$	$b_2 = b\omega_2$	$b_3 = b\omega_3$
Belief certainty (c)	$c_1 = c\omega_1$	$c_2 = c\omega_2$	$c_3 = c\omega_3$
Attribute evaluation (e)	$e_1 = e\omega_1$	$e_2 = e\omega_2$	$e_3 = e\omega_3$

As is apparent in these two tables, the directly measured variable B_1 fulfills two functions here: first, it captures part of the uniform influence of belief across attributes (b); second, it captures part of the influence of the importance of Attribute 1 (ω_1). The effect of belief (b) was jointly captured by beliefs across all attributes (B_1, B_2, and B_3). The same applies to the effects of belief certainty (c) and attribute evaluation (e). For the relative importance of Attribute 1 (ω_1), it was jointly captured by the belief about that attribute (B_1), the certainty of the belief about that attribute (C_1), and the evaluation of the attribute (E_1). The same applies to the relative importance of all other attributes.

This approach, therefore, allows us to consider the influence of belief importance without the concern of adding a redundant multiplicative variable into the model, which appears to be the actual issue that led Fishbein and Azjen (2010) to simplify their approach. Moreover, this approach helps circumvent the problem of multicollinearity, which will be discussed in greater detail in the next chapter.

In more general terms, this model posits that individuals' attitudes toward any particular piece of policy should be a function of what they believe that policy will do, how sure they are about their beliefs on what the policy will do, how much they like or dislike what they believe that policy will do, and how important those individual provisions are to them.

An identity-based perspective

Although the expectancy-value model of attitude makes a solid and convincing argument about the fundamental role of substantive information about an attitude object in individuals' formation of attitudes toward that object, a belief-based attitude model is not immune to challenges or debates. As a matter of fact, individuals are often able to reach preferences or draw conclusions not relying on awareness of or substantive information about the attitude object (Druckman, 2005; Lupia & McCubbins, 1998). A large body of literature suggests that heuristic cues and cognitive shortcuts often allow individuals to form attitudes and make decisions without going through a thorough optimization process as the expectancy-value model of attitude suggests (e.g., Lau & Redlawsk, 2001; Lodge et al.,1995; Lupia, 1994; McConnell et al., 2008; Mullinix, 2016). As Lupia and McCubbins (1998) summarized, "limited information need not prevent people from making reasoned choices … people can use substitutes for encyclopedic information" (pp. 4–5).

A variety of cognitive heuristics or cues might be leveraged by individuals in the formation of their policy attitudes (Lau & Redlawsk, 2001), among which the partisan cue is arguably the most prominent and consequential in American politics (Conover, 1981; Goren et al., 2009; Lavine et al., 2012; Schaffner & Sterb, 2002). Citizens need not understand the specifics of a policy in order to form an attitude toward it. Rather, their preference would be guided by the endorsement of or objection to the said policy from the political party with which they identify.

Theoretical support for the proposition that individuals will let partisan identities guide their policy preferences could be found in the holistic approach to understanding attitudes (Albarracin & Shavitt, 2018). Albarracin and Shavitt (2018) argue that attitudes exist in three fundamental contexts, namely the person, the social, and the broad. Whereas variations in beliefs, values, emotions, and goals in the context of the person could reasonably result in changes in attitudes, it is equally important, if not more, to consider the influences of the social context (e.g., social groups and networks) and the broad context (e.g., generation, history, and culture) on attitude formation and changes,

The belief-based model for how individuals might aggregate their beliefs in forming preferences, therefore, must contend with an alternative approach that positions contexts as the central element in attitude formation, among which the social identity perspective of attitudes might be of the greatest relevance to the current project (Chen & Li, 2009; Hogg & Smith, 2007;

Smith & Hogg, 2008). The social identity perspective of attitudes argues that individuals render judgments and form attitudes not by aggregating their beliefs and evaluations, but instead in response to social forces. As Smith and Hogg (2008) put it, “attitudes are normative and embedded in wider representational and ideological systems attached to social groups and categories … they are socially structured and grounded in social consensus, group memberships, and social identities” (p. 337).

In the context of public policy attitudes in the U.S., for example, Republicans may conclude that a piece of legislation must not be likable not because they know what the legislation will or will not do, but because they know that the Democratic Party endorsed the legislation while the Republican Party was opposed to it. In turn, when rendering their judgments, they could infer that the legislation would cause damaging consequences and choose to ignore positively valanced outcomes of the legislation to justify their attitudes.

To the extent that preferences are not guided by the belief-evaluation aggregation but the cue-taking processes, not only might (mis)beliefs not be a source of one’s attitudes, but they could even be a rationalized product thereof (Taber & Lodge, 2006). And when information is not used in rendering a judgment, whether informational beliefs are objectively accurate should have little to no relevance. Addressing misbeliefs would therefore be a considerable waste of time and effort.

In fact, an expanding body of work on biases in information processing provides reason to think that the importance of information accuracy may be overstated. Studies on partisan motivated reasoning have shown that individuals who encounter a piece of information that challenges their partisan identification will tend to counterargue against that information (Lodge & Taber, 2013), and can sometimes bolster pre-existing beliefs even when the new information contradicts those beliefs (Nyhan & Reifler, 2010; but see Wood & Porter, 2019). In practice, this means that members of different political parties might become aware of different pieces of information about policies corresponding with particular attitudes toward those policies. Individuals with different attitudes toward the same object would be expected to differ not only in their beliefs about this attitude object, but also in the partisan identities they seek to protect. Therefore, it is crucially important to test the effects of informational beliefs and partisan identities on political attitudes simultaneously. The current project will pit these two possibilities against each other by comparing the belief-based model and the identity-driven approach where individuals let their partisan identities guide their policy attitudes irrespective of their beliefs about what the policy will or will not do.

CHAPTER 3

A Bayesian Approach

The conceptual model

This dissertation, therefore, proposes the following conceptual model to test the formation of political attitudes:

$$Attitude \propto \sum_{i=1} (bce)\omega_i + \gamma + \sum_{m=1} \delta_m$$

where b represents the influence of belief, c represents the influence of belief certainty, e represents the influence of attribute evaluation, ω_i represents the relative importance of attribute i, γ represents the effect of partisan identity, and δ_m represents the effect of demographic covariate m.

As noted previously, b, c, e, and ω_i are extracted from b_i, c_i, and e_i. In practice, the model still needs to estimate b_i, c_i, and e_i for every individual attribute separately and to construct a matrix to decompose all b_i, c_i, and e_i into estimates for b, c, e, and ω_i. The interactions between belief, belief certainty, and attribute evaluation would increase the number of total parameters to be estimated per attribute to seven. If we were to consider how belief, belief certainty, evaluation, and their interaction effects associated with ten different attributes of the attitude object shape the overall attitude, we will be estimating 70 distinct parameters. In addition, we still need to estimate the effects of partisanship and a series of demographic covariates in the same model. With most survey samples, a traditional linear regression analysis could hardly make reasonable estimates of all these parameters without confronting the problem of overfitting (Harrell, 2001). Therefore, I turn to an alternative approach with the potential to accurately estimate this model, which is Bayesian analysis.

Bayes' theorem

Bayesian statistics is a branch of statistical inference that is different from traditional frequentist or likelihood approaches (Samaniego, 2010). At its core, it aims to update prior estimates of a parameter with new evidence (data) in a coherent manner (Gill, 2008).

Bayesian inference is built upon Bayes' theorem, which is a fundamental principle of conditional probability to calculate the probability of an event occurring given that another event has occurred (Bayes, 1763). Bayes' theorem can be expressed mathematically as follows:

$$\mathrm{P(H|E)} = \frac{\mathrm{P(E|H)} \cdot \mathrm{P(H)}}{\mathrm{P(E)}}$$

where $\mathrm{P(H|E)}$ is the probability of the hypothesis H being true given the evidence E, $\mathrm{P(E|H)}$ is the probability of observing the evidence E if the hypothesis H is true, $\mathrm{P(H)}$ is the initial probability of the hypothesis H being true before considering the evidence E, and $\mathrm{P(E)}$ is the marginal probability of the evidence E, which can be calculated as the sum of the probabilities of observing E across all possible hypotheses.

For the rest of the discussion, $\mathrm{P(H|E)}$ will be referred to as the posterior probability, $\mathrm{P(E|H)}$ will be referred to as the likelihood, and $\mathrm{P(H)}$ will be referred to as the prior probability. Bayes' theorem, therefore, aims to calculate the posterior probability through multiplying the prior probability by likelihood and then dividing by the total probability of observing the evidence. In other words, the posterior probability distribution is proportional to the product of the prior probability distribution and the likelihood function, which means that the posterior reflects both the initial beliefs based on prior knowledge and the new evidence provided by the data (McElreath, 2020). In contrast, frequentist statistics do not explicitly consider prior knowledge or information (Casella & Berger, 2002). In practice, Bayesian statistics answer the question of what we should now believe given both our preexisting views and the new data whereas frequentist statistics only answer questions about what the new data indicates.

Basic procedures

The first step in Bayesian inference is to formulate a prior probability distribution, which represents the initial belief or knowledge about the parameters of interest before observing any (new) data. The prior can be informative, based on expert opinion, previous research, or reasonable assumptions. Or the prior can be non-informative, reflecting little to no prior knowledge.

The next step is to specify the likelihood function, which describes how the data is generated given the model parameters. It represents the probability of observing the data for different parameter values. The likelihood function is a fundamental component of both Bayesian and frequentist statistics.

When a non-informative prior probability distribution and a maximum likelihood function are adopted, the parameter estimates generated by a Bayesian analysis should be very similar to its frequentist counterpart (Kass & Wasserman, 1996). However, one of the advantages of Bayesian analysis in comparison to the frequentist approach is that it allows the possibility to incorporate informative prior probability distribution and different likelihood functions into the model, if we have strong knowledge or reasonable assumptions to support and justify the choices of informative priors and/or likelihood functions.

Estimation of parameters

Another difference between Bayesian analysis and the traditional frequentist approach—arguably a major advantage of Bayesian methods, at least for the purpose of the current study—is that they see parameters and compute parameter estimates in fundamentally different ways. Traditional frequentist approaches consider parameters, such as the mean or variance, to be fixed but unknown quantities (Casella & Berger, 2002). The goal of frequentist inference, therefore, is to estimate these fixed parameters using the data obtained from a sample. There might be errors in the results due to errors or biases in the procedure of drawing samples from the population. Nevertheless, theoretically speaking, there is a fixed, correct value for every single parameter.

In contrast, Bayesian analysis does not see any parameter as having a single true value. Instead, Bayesian statistics consider parameters as random effects with a range of values within which the correct estimate might fall in (Casella & Berger, 2002; Gill, 2008). Bayesian inference, therefore, aims to generate a full probability distribution of the parameters (i.e., the posterior probability distribution), which represents the updated beliefs about the parameters (e.g., the mean value) after observing the data and quantifies the uncertainty in the parameter estimates (e.g., the variance or standard deviation) by taking into account both the prior knowledge and the data (Gelman et al., 2013). Therefore, technically speaking, Bayesian analysis can circumvent the problem of overfitting and estimate an enormous number of parameters (Carlin & Louis, 2009).

From this perspective, Bayesian analysis is to a great extent similar to the hierarchical or multi-level modeling analysis estimating random effects. The difference is that hierarchical modeling treats only some of the parameters as random effects while other parameters are modeled as fixed effects, whereas Bayesian analysis regards all parameters as random variables with associated probability distributions (McElreath, 2020).

Interpretation of probability

A collateral benefit of how Bayesian analysis estimates parameters is that it offers a more straightforward and intuitive way to understand and interpret the results. In the frequentist paradigm, probability is interpreted as the long-run frequency of an event occurring across repeated samples or experiments. This means that the probability of an event is the proportion of times it would occur across a large number of repeated trials. This is a point of considerable confusion, as it means that, contrary to what many students of statistics initially think, a 95% confidence interval (CI) does not actually imply that the value of the parameter of interest has a 95% chance of falling into the denoted range. Instead, it indicates the range of values within which the true parameter is likely to fall for 95 of 100 hypothetical repeated trials, which is both difficult and counter-intuitive in terms of interpretation.

Bayesian analysis, however, generates a posterior probability distribution for every parameter. The highest density interval (HDI) of the posterior probability distribution, which is the Bayesian equivalent to CI, specifies the range of values generated for the parameter of interest above and below the point estimate (Gelman et al., 2013). The posterior probability is therefore a degree of credibility or plausibility about the parameter value (McElreath, 2020). 95% HDI, for example, represents the range of parameter values that contains 95% of the probability mass from the posterior distribution, which literally means that there is a 95% probability that the true parameter value lies within the interval (presuming the model was correctly specified), yielding a much clearer way of interpreting the results (Jaynes, 2003).

Computation of results

With the prior probability distribution (either informative or non-informative) and the likelihood function, Bayesian inference then involves using certain algorithms to compute the posterior probability distribution for any given parameter, among which Markov Chain Monte Carlo (MCMC) methods currently dominate. In fact, many would argue that the resurgence of research on and applications of Bayesian statistics more than 200 years after Thomas Bayes proposed his now-eponymous theorem could largely be attributed to the discovery of MCMC methods such as the Metropolis-Hastings algorithm and the Hamiltonian Monte Carlo algorithm in the late 20th century (Geyer, 2003; Robert & Casella, 2011).

The core idea of MCMC is to construct a Markov chain, a sequence of random variables where each variable depends only on its immediate predecessors, with the desired posterior distribution as its stationary distribution (Jackman, 2000a). After a sufficiently long "burn-in" period, the Markov chain converges to its stationary distribution, and samples drawn from the chain can then be used to compute the results of parameter estimates.

A general analogy of this computation process is that MCMC methods take a random walk in a multidimensional space for each of the parameter estimates (Robert & Casella, 2004). The parameter estimate starts at a random initial point in the space. It then proposes a new candidate sample for the parameter from a proposed distribution (e.g., Gaussian) centered around the current sample, which corresponds to considering a step in a random direction in this multidimensional space (Chib & Greenberg, 1995).

To determine whether or not to take that step (and adjust the parameter value accordingly), the algorithm calculates an acceptance probability. Specifically, it compares the probability of observing the current position across all variables with the probability of observing the position after the random step under consideration based on the data. The propensity to accept the proposed step is then determined as a function of the ratio of these two probabilities. If the new parameter estimate is more likely than the old, the algorithm will tend to accept the estimate whereas if the new estimate is less likely than the old, the algorithm is more likely to reject it, thereby retaining the current parameter estimate (McElreath, 2020).

This process is then repeated for a predetermined number of iterations, constructing a random walk through the parameter space, where the probability of arriving at each point in the space corresponds with the relative likelihood of that parameter value. If we have a sufficient number of iterations, or in other words, let the random walk continue long enough, the algorithm should be able to effectively explore the whole space, during which regions with higher probability will be visited more frequently (McElreath, 2020). As the chain progresses, it will converge to the stationary distribution, which is the target distribution we want to sample from.

After the chain converges and reaches its stationary distribution, the walk will continue and samples will then be collected from these iterations. Averaging these samples will generate estimates for parameters of interest. The narrowest interval that contains a desired percentage of samples for parameter estimates could also be identified. The interval with the smallest width represents the range within which the parameter is most likely to lie, which is the HDI.

The applicability of Bayesian statistics in the current project

Bayesian methods' capabilities to incorporate informative prior probability distribution and to compute posterior probability distribution make it an ideal statistical approach to address the methodological challenges for this dissertation project.

One of the reasons that the original expectancy-value model of attitude cannot thoroughly examine how multiple beliefs and evaluations associated with different attributes of the attitude object might collectively shape the overall attitude is that some of these beliefs and evaluations might be closely related and therefore cause the problem of multicollinearity. For example, a COVID-19 policy might contain three components—a mask mandate (Attribute 1), a vaccination mandate (Attribute 2), and a mandate on self-isolation after potential exposure to the disease (Attribute 3). Evaluations of these three components of the policy are likely to be highly correlated with one another. It is not unreasonable to assume that individuals who favor a mask mandate will probably also support a vaccination mandate, and people who hate the idea of wearing a mask will probably also reject isolating themselves even if they are potentially contagious. Therefore, when we attempt to assess how the evaluations of these three components (e_1, e_2, and e_3) collectively shape people's overall attitude toward the policy, estimates for the values of these parameters will not be independent and our conclusions about them are likely to be inaccurate.

The solution proposed by the current dissertation to address this multicollinearity problem is that attribute evaluation (as well as belief and belief certainty) is seen as having structurally similar relation with the overall attitude across all attributes of the attitude object, and the unique contribution of the evaluation of each individual attribute will be determined by the relative importance of that attribute.

Therefore, each e_i (the effect of the evaluation of attribute i) should be considered as the result of e (the uniform influence of evaluation) being weighted by ω_i (the relative importance of attribute i). The same applies to all b_i (the belief about attribute i) and c_i (the certainty of belief about attribute i) as well. Therefore, in the inference process, a regulating structure must be imposed to specify these relationships between variables, as demonstrated in the following matrix:

Table 3.1 *Structural Constraints on the Relations between Belief, Belief Certainty, Attribute Evaluation, and Attribute Importance*

Effect of variable	Attribute importance (ω_i)				
	ω_1	ω_2	ω_3	…	ω_i
Belief (b)	$b_1 = b\omega_1$	$b_2 = b\omega_2$	$b_3 = b\omega_3$	…	$b_i = b\omega_i$
Belief certainty (c)	$c_1 = c\omega_1$	$c_2 = c\omega_2$	$c_3 = c\omega_3$	…	$c_i = c\omega_i$
Attribute evaluation (e)	$e_1 = e\omega_1$	$e_2 = e\omega_2$	$e_3 = e\omega_3$	…	$e_i = e\omega_i$

There is no easy way to impose such a matrix structure in traditional regression analysis to regulate the relationships between parameters. However, in Bayesian statistics, we can conveniently incorporate this as a part of the prior probability distributions to compute the posterior probability distributions for all the parameters.

And because b, c, e, and ω_i are extracted from b_i, c_i, and e_i, the values of ω_i must be within a limited range so that the computation of b, c, e, and ω_i through decomposing b_i, c_i, and e_i could be carried out in a reasonable manner, otherwise, there will be an infinite number of possible solutions to the matrix in Table 3.1. Since ω_i represents the relative importance of attribute i, an informative prior with possible values ranging from 0 to 1 for ω_i will be adopted in the following analyses. It is reasonable to assume that under rare circumstances some attributes could be considered negatively important, and an upper limit of 1 simply provides a reference point because importance is always relative.[2]

Lastly, as discussed before, even though the parameters of interest, after this structural transformation, have been changed into b, c, e, and ω_i, in practice, all b_i, c_i, and e_i for every individual attribute i still need to be calculated, which is a considerable amount of parameters. The Bayesian approach of calculating posterior probability distribution for any given parameter, as previously explained, could bypass the potential overfitting problem in traditional regression

[2] If the maximum importance were set to 2 instead of 1, for example, we could achieve the exact same predictions by simply having the estimates for the values of b, c, and e. The result would be the exact same equation and estimates, with an identical series of interpretations. Faced with multiple equal-fitting solutions, unconstrained algorithms would yield inconsistent estimates even though the substantive results would be identical.

analysis, and generate accurate point estimates and HDIs for all the parameters. Considering all this, Bayesian analysis is an appropriate approach for the current project and will be adopted to construct and test the proposed model of political attitude formation.

CHAPTER 4

An Overview of American Public Opinion on the ACA

After reviewing relevant theories of attitude formation in Chapter 2 and Bayesian methods in Chapter 3, this chapter marks the start of empirical analyses in this dissertation. In this chapter, I will introduce the data collection procedures, detail the operationalizations of key measures, and offer a descriptive examination of the key variables in this project, including the state of information (belief accuracy and belief certainty) and provision evaluations, as well as the partisan variations in the distributions of these variables.

Data

Data collection

Data for the current study come from a nationally representative survey conducted by GfK on behalf of the Associated Press. GfK's KnowledgePanel® (now part of IPSOS) is a nationwide probability-based sample of American adults recruited via random-digit-dialing telephone (RDD) and postal mail sent to a set of addresses sampled from the United States Postal Service's Computerized Delivery Sequence file.[3] Upon joining the panel, people were asked to complete a core profile questionnaire about their age, gender, race, ethnicity, education, income, and other demographic information. For each individual survey, respondents were selected from the panel using a probability proportional to size weighted sampling design, yielding a sample

[3] Today, the sample is entirely recruited using address-based sampling, but RDD was used in some early phases and represented a moderate proportion of the panel during the survey period.

that is representative of the American population. Panel members were remunerated for regularly completing surveys online. A tablet and Internet access were provided for panelists who did not have one.

The survey analyzed in the current study was conducted between August 3 and 13, 2012. GfK invited a random sample of 2,344 American adults from their panel to participate, and 1,344 completed the questionnaire, yielding a completion rate of 57.3% and a cumulative response rate (accounting for panel recruitment) of 6.1% (CUMRR1, see Callegaro & DiSogra, 2008). The median time spent on completing the questionnaire was 17 minutes. Table 4.1 reports the information on response rates.

Table 4.1 *Response Rates*

Category	Rate
Recruitment rate (RECR)	17.2%
Profile rate (PROR)	61.5%
Completion rate (COMR)	57.3%
Active rate	99.2%
Cumulative response rate 1 (CUMRR1; RECR × PROR × COMR)	6.1%

Missing data

Although the majority of respondents answered all of the questions, some individuals failed to do so at least some of the time. If every respondent who failed to answer at least one question were removed from the analysis, 23.7% of respondents would be omitted, which would be a considerable loss of data.

This dissertation, therefore, used multiple imputation by chained equations (MICE) method to impute these missing values. The MICE method has been shown to significantly improve model estimates compared to listwise deletion procedures because listwise deletion would seriously compromise statistical power and would cause non-random case elimination, which is important for making inferences to the entire population (Collins et al., 2001; Little & Rubin, 2002; Schafer & Graham, 2002).

MICE is an iterative algorithm that employs multiple imputations to estimate missing values in a dataset, resulting in a more complete dataset that can be used for Bayesian analysis. The basic idea is to replace each missing value with a set of plausible values, create multiple complete datasets, and then analyze these datasets. The results from these analyses are combined to produce a single estimate, where the variations across datasets are treated as adjustments to account for the uncertainty introduced by the missing data (van Buuren & Groothuis-Oudshoorn, 2011). The method assumes that data are missing at random (MAR), meaning that the probability of a value being missing is related to the values of the observed data but not uniquely to whether or not a piece of data is missing.[4] It then uses a series of regression models to predict missing values, based on the observed values in the dataset.

The first step of MICE is to replace missing values with an initial guess. This initial imputation creates a complete dataset that serves as the starting point for the iterative process. MICE then employs a series of regression models to predict missing values based on the observed values in the dataset. The iterative imputation process will set one variable with missing data as the target variable and consider the other variables as predictors. It will then use the observed values (not imputed) of the target variable and the complete cases of the predictors to fit a regression model. It can thus predict the missing values in the target variable using the fitted model, and will replace the missing values in the target variable with a sample from the distribution of the predicted values for each case. This step will be repeated for a specified number of iterations, refining the imputations at each iteration.

[4] In practice, analyses suggest that using this set of assumptions is actually better than listwise deletion even if missingness is not truly random when covariates have been accounted for (see King et al., 2001).

After completing this iterative imputation process, the final imputed dataset will be saved, which represents one version of the missing data imputed using MICE. And to account for the uncertainty associated with the missing data, the iterative imputation process will be repeated multiple times, generating multiple imputed datasets. This process is expected to generate new datasets where each missing value properly captures both the relations among variables and the error in the estimates of those relations. The presence of multiple datasets also allows us to assess how variable the imputation process is likely to be and to adjust the uncertainty of parameter estimates generated from the model accordingly (van Buuren & Groothuis-Oudshoorn, 2011). Desired statistical analysis will then be performed on all the imputed datasets to obtain estimates for parameters of interest. By iteratively refining imputations through chained equations and accounting for uncertainty due to missing data, MICE can produce more accurate and efficient estimates compared to traditional techniques like list-wise deletion (Graham, 2009; Rubin, 1987; Schafer & Olsen, 1998).

For the current project, five iterations were specified for the imputation of any missing value, and five imputations were conducted, both of which are commonly accepted practices for the MICE method (van Buuren, 2018). As a result, five imputed datasets were generated and retained, yielding a total of 6,720 cases for all following analyses performed in this dissertation.[5]

Measures

Attitude toward the ACA

To understand individuals' attitudes toward the ACA, respondents were asked, "In general, do you favor, oppose, or neither favor nor oppose the law changing the health care

[5] Because most of the results in this dissertation are focused on generating mean values, it makes sense to generate estimates across all 5 imputations rather than generating results for only a single imputation. Inferential statistics need to be corrected to account for the true N of 1,344 cases so that statistical precision is not inflated.

system that the U.S. Congress passed in March 2010?" Response options were, "Favor strongly" (coded: 1), "favor somewhat" (.75), "neither favor nor oppose" (.5), "oppose somewhat" (.25), and "oppose strongly" (0).

Beliefs about the ACA components

To assess beliefs about the ACA components, respondents were asked whether each of the 18 statements described things that the ACA would do. Public debate about the ACA called attention to many aspects of the law that were included in the version that Congress passed. In addition, during the course of public debate, a number of inaccurate claims were made, asserting that the bill included provisions that were not included in the final version. In this survey, respondents were asked to indicate whether they believe the new health care law would implement 18 different requirements. Of the 18 provisions, 12 were principal provisions that were part of the ACA. They were carefully selected to cover most of the central elements of the law based on a report by the KFF (2012) which summarized key elements of the law as well as changes made to the law by subsequent legislations. The remaining six questions asked about provisions that were often rumored to be in the ACA but actually not. False claims about these provisions have frequently appeared in media coverage and public debates. These provisions were selected by experts at the Associated Press and researchers at Stanford University. Response options to these 18 questions were either "the law will do this" (coded: 1) or "the law will not do this" (0). The order of the questions was randomized across respondents. Table 4.2 lists all 18 questions assessing respondents' beliefs about the ACA components.

Table 4.2 *Summary of Provisions*

	Abbreviation	Full wording
Provisions in the ACA	Individual mandate	Require that if a U.S. citizen does NOT have health insurance, that person will have to pay a fine on his or her federal income taxes unless he or she is allowed not to have the insurance for a series of specific reasons, such as having a very low income
	Employers must provide	Require companies with 50 or more employees to provide health insurance to their employees or pay a fine to the federal government if they do not
	Subsidize low income	Give money to pay for health insurance to people who are U.S. citizens and have very low incomes
	Small business tax credits	Give federal tax credits to some very small companies if they buy health insurance for their employees
	Drug companies fee	Require companies that make drugs to pay new fees to the federal government each year
	Insurance companies fee	Require companies that sell health insurance to pay new fees to the federal government each year
	No preexisting condition denial	Require health insurance companies to sell health insurance to U.S. citizens and legal immigrants who don't have health insurance and have a serious medical problem
	Cover under 26	Allow young adults to get health insurance by being included in their parents' health insurance policies until they turn 26
	No capped coverage	Prevent a health insurance company from limiting the amount of money that it will pay for a person's health care costs during his or her life
	No dropped coverage	Require a health insurance company to continue a person's health insurance as long as he or she pays for it and has not broken any rules of the health insurance plan
	Make insurance for sale	Make health insurance available for sale so that any American can buy if he or she wants to
	Subsidize seniors	Provide discounts on prescriptions to seniors with high drug costs
Provisions NOT in the ACA	ID Card	Require every American to show a government health care identification card in order to get medical care at a hospital
	Disclose illness to employers	Require that anyone applying for a job must tell the employer if he or she has ever had any serious diseases
	Soda tax	Require that fast food restaurants that sell unhealthy food or drinks to pay a fee to the federal government
	Death panel	Create committees of people who will review the medical histories of some people and decide whether they can get medical care paid for by the federal government
	Smoker fee	Require insurance companies to charge an additional fee of $1,000 to anyone who buys insurance from them and smokes cigarettes
	Undocumented immigrants free	Require some doctors and hospitals to treat illegal immigrants free of charge if they cannot afford to pay

Certainty of beliefs

To determine the certainty with which respondents held their beliefs about the ACA, they were asked to provide this information about each provision. After answering the belief question about each provision, respondents were asked, “How sure are you about that?” Response options were: “Extremely sure” (coded: 1), “Very sure” (.75), “Moderately sure” (.5), “Slightly sure” (.25), and “Not sure at all” (0).

Provision evaluation

To ascertain what respondents thought about various components of the law, they were asked whether they liked each of the provisions. After answering all of the belief and belief certainty questions, respondents were asked a second set of questions about what they thought about the provisions. In this set of questions, respondents were presented with each provision again and were asked, “Do you favor or oppose this change?” Response options were: “Strongly favor” (coded: 1), “Somewhat favor” (.5), “Neither favor nor oppose” (0), “Somewhat oppose” (-.5), and “Strongly oppose” (-1).

Partisanship

Following these questions about beliefs and evaluations, respondents were asked two questions to assess their party identification. First, they were asked, “Do you consider yourself a Democrat, a Republican, an Independent, or none of these?” In the questionnaire, the sequence of “Republican” and “Democrat” changed randomly for different respondents to avoid any potential order or priming effects. Response options were “Democrat,” “Republican,” “Independent,” and “None of these.” If respondents chose “Democrat” or “Republican,” they were then asked, “Do you consider yourself a strong [Democrat/Republican] or a moderate [Democrat/Republican]?” If respondents chose “Independent” or “None of these,” they were then asked, “Do you lean toward the Democrats or the Republicans, or don’t you lean either way?” Response options were “Lean toward the Democrats,” “Lean toward the Republicans” and “Don’t lean either way.” Response options were then recoded into a seven-point scale ranging from strong Republican (coded: 0) to strong Democrat (1), with no-lean Independent at .5.

Demographics

Demographic variables were asked at the end of the survey. Age was coded to range from 0 to 1. Dummy variables distinguished between White, Black, Hispanic respondents, and those who indicated they belonged to another ethnic group. An education variable separated respondents into four groups—those who received some high-school education or less, those who completed high-school education with a degree, those who received some college education but no degree, and those who graduated from college. Finally, an income variable distinguished respondents who indicated having low income (less than $39,999), moderate income (between $40,000 and $84,999), or high income (more than $85,000).

How much do people know about the ACA?

Before analyzing how individuals’ beliefs about the components of the ACA, the level of certainty associated with each belief, and the extent to which they like or dislike those components, might collectively shape their overall attitudes toward the law, it is important to review what their beliefs about and evaluations of those individual provisions actually are. This allows us to have a basic understanding of both Americans’ informational beliefs and their feelings about what they believe the ACA will or will not do, which are the foundational elements in the model that this dissertation proposed. In the rest of this chapter, I provide detailed descriptive analyses of Americans’ state of information about and evaluations of the law.

When we assess the correctness of people's beliefs about the ACA provisions without considering the certainty of those beliefs, as how most past studies gauging political knowledge do, it seems that Americans generally demonstrated a rather high level of awareness of the law. There was considerable variability across provisions, but the majority of answers were correct for 15 out of the 18 questions (Column 1, Table 4.3). More than 80% of respondents correctly identified that the ACA would allow children under age 26 to be covered by their parents' insurance policies. Similar majorities were aware that the ACA would require companies with more than 50 employees to provide health insurance and that the law would prevent insurance companies from terminating coverage for people who had not missed payments. Misperceptions dominated for three questions: respondents were not aware that insurance companies would be charged new fees, that there would be new fees for pharmaceutical companies, and that the ACA would not require health care providers to treat undocumented immigrants for free. It is also worth noting a not insignificant proportion of respondents believed that the so-called "death panel" was real.

These numbers should not be unreservedly taken as indicating respondents' true state of information regarding the ACA though. For one, these questions only offered two answer choices (in the law vs. not in the law). A random guess would thus be expected to produce 50% of correct answers. As revealed in Table 4.3, 55.7% of the respondents correctly identified that the ACA would subsidize low-income citizens to pay for health insurance, and 58.3% of the respondents correctly identified that the ACA would not set up a "death panel," both of which were minimally higher than what would be expected by chance alone. Therefore, it might be inappropriate to assert that the respondents really possess these beliefs. The certainty with which they hold these beliefs should be considered to evaluate their information state more rigorously.

Table 4.3 *Informedness by Provisions (Correctness)*

Provision	Percentage of respondents correct	Percentage of respondents correct with high certainty
Provisions in the ACA		
Cover under 26	85.7%	57.9%
Employers must provide	83.9%	41.6%
No dropped coverage	81.3%	31.0%
No preexisting condition denial	77.1%	35.1%
Individual mandate	73.1%	39.3%
Make insurance for sale	72.9%	30.7%
Small business tax credits	70.6%	18.9%
Subsidize seniors	69.1%	20.7%
No capped coverage	63.0%	26.2%
Subsidize low income	55.7%	19.5%
Insurance companies fee	44.0%	11.0%
Drug companies fee	39.6%	10.9%
Provisions NOT in the ACA		
Disclose illness to employers	79.7%	27.7%
Soda tax	77.5%	25.3%
Smoker fee	68.7%	15.9%
ID Card	59.4%	14.4%
Death panel	58.3%	19.2%
Undocumented immigrants free	42.9%	11.5%

Note. "High certainty" includes respondents who reported either "very sure" or "extremely sure" about the answers they gave to corresponding belief questions.

When the certainty level associated with beliefs was taken into consideration, the picture changed tremendously. First, most answers given by respondents to these belief questions were accompanied by only a modest level of certainty. Regardless of accuracy, 17.6% of all answers given were "not sure at all," 16.1% were "slightly sure," 33.1% were "moderately sure," 18.5% were "very sure," and only 14.7% were "extremely sure." And among the 12 provisions in the law, only one provision was correctly identified as being part of the ACA by a majority of the respondents with high certainty (i.e., very sure or extremely sure), namely that young adults under age 26 could get health insurance by being included in their parents' policies. Apart from the "cover under 26" provision and the provision that large companies were required to provide health insurance to employees, no provision was correctly identified as being part of the law with high certainty by more than 40% of respondents.

The situation is even more concerning for provisions that were rumored to be but actually not part of the ACA. Not a single provision was correctly identified as a false claim with high certainty by more than 30% of the respondents. In fact, only 19.2% of respondents confidently said that the ACA would not instate a "death panel," and only 11.5% of respondents knew for sure that the ACA would not offer undocumented immigrants free medical treatments.

Table 4.4 *Informedness by Provisions (Incorrectness)*

Provision	Percentage of respondents incorrect	Percentage of respondents incorrect with high certainty
Provisions in the ACA		
Cover under 26	14.3%	3.2%
Employers must provide	16.1%	2.5%
No dropped coverage	18.7%	3.4%
No preexisting condition denial	22.9%	4.9%
Individual mandate	26.9%	6.4%
Make insurance for sale	27.1%	8.7%
Small business tax credits	29.4%	5.6%
Subsidize seniors	30.9%	8.6%
No capped coverage	37.0%	7.0%
Subsidize low income	44.3%	9.3%
Insurance companies fee	56.0%	6.9%
Drug companies fee	60.4%	6.4%
Provisions NOT in the ACA		
Disclose illness to employers	20.3%	6.3%
Soda tax	22.5%	6.8%
Smoker fee	31.3%	9.2%
ID Card	40.6%	13.3%
Death panel	41.7%	12.8%
Undocumented immigrants free	57.1%	18.8%

Note. "High certainty" includes respondents who reported either "very sure" or "extremely sure" about the answers they gave to corresponding belief questions.

Through a different lens, it is evident that for provisions in the law, no incorrect belief was firmly held by more than 10% of the respondents, as indicated in Table 4.4. Even in the case of the provision regarding new fees for pharmaceutical companies, which was mistakenly identified as not being in the law by 60.4% of respondents, only a small fraction (6.4%) held this misbelief with a high level of certainty. However, greater concern arises from respondents who confidently embraced incorrect beliefs about provisions that were not part of the law. 18.8% of respondents firmly believed that the ACA mandated free treatment for undocumented immigrants, constituting one-third of those holding this erroneous belief. Additionally, 13.3% and 12.8% of respondents confidently believed that the ACA would impose a nationwide health care identification card requirement and that the so-called "death panel" is real.

But how was the information about these provisions distributed? The accuracy levels presented above can be explained by two possible processes. It is possible that some Americans knew a lot about the ACA whereas others were largely uninformed. In contrast, it could be the case that most Americans knew a moderate amount about the law and that relatively few were either extremely informed or completely ignorant. To understand this, we can look at how many questions were accurately answered by different respondents, as well as how respondents varied in confidence in their own answers.

From this vantage point, 81.8% of respondents answered more than half of the 18 belief questions correctly (i.e., better than chance; Column 2, Table 4.5), but only 46.5% answered 13 or more of the 18 questions correctly (i.e., a correctness rate of over 70%). And these figures were strikingly lower if we consider these correct beliefs as being "really" held by respondents only when the correct answers were given with high certainty: 14.0% and 3.6%, respectively (Column 4, Table 4.5). Not a single respondent answered every belief question correctly with high certainty, nor did any respondent give confidently correct answers to all questions with only a single mistake. In fact, very few respondents were able to answer all or nearly all of the questions correctly even if certainty was not considered (0.3% and 1.6% respectively). On the contrary, over 20% of the respondents did not express confidence in any correct answers. The huge discrepancy in these numbers raises alarm about the traditional way that most past studies used to assess the state of people's political knowledge and state of information, because those quiz-type questions could inflate the knowledgeability or informedness of individuals who lack genuine understanding but coincidentally arrive at correct answers by guessing.

Table 4.5 *Informedness by Total Number of Correct Answers*

Number of correct answers	Regardless of certainty		High certainty	
	Percentage	Cumulative percentage	Percentage	Cumulative percentage
All 18	0.3%	0.3%	0%	0%
17 out of 18	1.6%	1.9%	0%	0%
16 out of 18	6.7%	8.6%	0.2%	0.2%
15 out of 18	11.3%	19.9%	0.8%	1.0%
14 out of 18	13.4%	33.3%	1.4%	2.4%
13 out of 18	13.2%	46.5%	1.2%	3.6%
12 out of 18	15.0%	61.5%	3.4%	7.0%
11 out of 18	12.3%	73.8%	2.9%	9.9%
10 out of 18	8.0%	81.8%	4.1%	14.0%
9 out of 18	5.9%	87.7%	5.6%	19.6%
8 out of 18	5.4%	93.1%	5.6%	25.2%
7 out of 18	3.1%	96.2%	6.0%	31.2%
6 out of 18	2.4%	98.6%	6.8%	38.0%
5 out of 18	0.8%	99.4%	6.2%	44.2%
4 out of 18	0.4%	99.8%	7.4%	51.6%
3 out of 18	0.1%	99.9%	8.8%	60.4%
2 out of 18	0.1%	100%	8.6%	69.0%
1 out of 18	0%	100%	10.7%	79.7%
0 out of 18	0%	100%	20.3%	100%

Note. "High certainty" includes respondents who reported either "very sure" or "extremely sure" about the answers they gave to corresponding belief questions.

What do people think of the ACA provisions?

Earlier studies revealed that Americans liked many key components of the ACA even while they opposed the law overall (e.g., Brodie et al., 2010; Deane et al, 2011). Results from analyzing the data for the current study echoed this finding. The overall attitude toward the ACA was slightly negative (M = .46, SD = .35, measured on a 0 to 1 scale). Yet as demonstrated in the first column of Table 4.6, nine out of the 12 provisions that were in the ACA received net positive ratings, with an average rating of .32 (*SD* = .59, measured on a -1 to 1 scale), and a majority of respondents either somewhat favored or strongly favored eight out of the 12 provisions. The mean evaluation across all the provisions in the law was positive as well.

Table 4.6 *Evaluations of Provisions*

Provision	Evaluation – Mean (SD)	Evaluation – Percentage favoring
Provisions in the ACA	.32 (.59)	-
No dropped coverage	.72 (.45)	86.0%
Make insurance for sale	.66 (.47)	81.3%
Subsidize seniors	.65 (.49)	81.9%
Small business tax credits	.52 (.51)	76.4%
Cover under 26	.51 (.59)	72.3%
No capped coverage	.44 (.66)	67.3%
No preexisting condition denial	.39 (.61)	65.0%
Employers must provide	.19 (.71)	55.0%
Subsidize low income	.14 (.69)	48.8%
Drug companies fee	-.05 (.63)	29.9%
Insurance companies fee	-.13 (.60)	24.3%
Individual mandate	-.22 (.73)	30.6%
Provisions NOT in the ACA	-.29 (.67)	-
Smoker fee	-.06 (.71)	36.6%
ID Card	-.16 (.70)	29.4%
Soda tax	-.25 (.69)	25.3%
Undocumented immigrants free	-.33 (.65)	21.2%
Death panel	-.43 (.63)	17.6%
Disclose illness to employers	-.49 (.61)	14.0%
All provisions	.12 (.62)	-

Note. “Favoring” includes respondents who reported either “somewhat favor” or “strongly favor” toward the provision.

On the contrary, all the provisions that were not in the ACA have been consistently evaluated unfavorably, with an average rating of -.29 (*SD* = .67). Five out of these six provisions were favored by less than 30% of the respondents (Column 2, Table 4.6). The notorious “death panel” myth received a negative evaluation of -.43 (*SD* = .63), and the most unwelcome provision was the false claim that the ACA will require anyone applying for a job to tell the employer if he or she has ever had any serious diseases (*M* = -.49, SD = *.61*).

Altogether, these numbers supported the concern that the slightly negative overall attitude toward the ACA might not be because Americans disliked what the law would do in reality. Instead, the components which have been falsely claimed to be part of the ACA and were disliked by the public might have substantially undermined the law's overall favorability to the extent that they were contributing to a negative overall attitude.

How do partisans differ?

The next question to be answered would naturally be whether there exists a partisan gap, especially in terms of the accuracy of people's beliefs about the ACA. To put it short, there are partisan differences across individual provisions, but it does not appear that any particular group was consistently better-informed than others.

Table 4.7 *Informedness Regardless of Certainty by Partisan Groups*

Provision	Percentage of respondents correct		
	Republicans	Independents	Democrats
Provisions in the ACA			
Cover under 26	87.7%	84.1%	86.2%
Employers must provide	87.9%	83.2%	81.5%
No dropped coverage	78.9%	79.1%	86.1%
No preexisting condition denial	78.8%	76.2%	76.8%
Individual mandate	78.1%	74.4%	67.2%
Make insurance for sale	64.1%	72.3%	81.0%
Small business tax credits	62.0%	67.8%	81.3%
Subsidize seniors	62.3%	67.1%	77.2%
No capped coverage	64.1%	58.0%	68.5%
Subsidize low income	62.0%	60.0%	57.7%
Insurance companies fee	48.3%	46.6%	37.1%
Drug companies fee	47.1%	39.3%	33.6%
Provisions NOT in the ACA			
Disclose illness to employers	73.9%	78.1%	86.5%
Soda tax	69.4%	80.5%	80.3%
Smoker fee	63.2%	68.1%	73.9%
ID Card	54.9%	59.2%	63.5%
Death panel	45.3%	56.8%	71.0%
Undocumented immigrants free	30.5%	43.0%	53.0%

As shown in Table 4.7, among the 12 provisions that were in the law, Democrats were more accurate in identifying five of them than Republicans, while Republicans were more accurate in identifying another five, and there was virtually no difference in correctly identifying two of the best-known provisions: that children under age 26 could stay on their parents' insurance plans, and that insurance companies cannot deny coverage because of pre-existing conditions.

Table 4.8 *Informedness with High Certainty by Partisan Groups*

Provision	Percentage of respondents correct with high certainty		
	Republicans	Independents	Democrats
Provisions in the ACA			
Cover under 26	58.8%	56.6%	58.9%
Employers must provide	47.3%	41.0%	37.7%
No dropped coverage	26.9%	28.8%	37.3%
No preexisting condition denial	36.0%	33.3%	36.8%
Individual mandate	44.6%	40.5%	33.3%
Make insurance for sale	22.6%	31.2%	36.9%
Small business tax credits	12.3%	17.8%	25.9%
Subsidize seniors	17.2%	17.1%	28.2%
No capped coverage	26.6%	23.6%	29.1%
Subsidize low income	21.2%	16.6%	21.7%
Insurance companies fee	12.9%	11.9%	8.3%
Drug companies fee	12.2%	11.3%	9.4%
Provisions NOT in the ACA			
Disclose illness to employers	21.4%	26.4%	34.5%
Soda tax	17.5%	24.8%	32.4%
Smoker fee	8.9%	15.0%	22.8%
ID Card	9.3%	14.9%	18.0%
Death panel	11.2%	17.2%	28.5%
Undocumented immigrants free	6.2%	11.4%	15.9%

Note. "High certainty" includes respondents who reported either "very sure" or "extremely sure" about the answers they gave to corresponding belief questions.

The situation changed tremendously for provisions that were not in the law. For all six provisions, Republicans were much more likely to erroneously identify them as part of the ACA than both Democrats and Independents (Table 4.7), and the pattern holds when we take certainty associated with each of those beliefs into consideration (Table 4.8). Therefore, it might be prudent to say that it is not that a group of respondents with any particular partisan identity was generally more *knowledgeable* about the ACA; however, Republicans were apparently more *misinformed* about the ACA as they were more likely to believe that the law would implement requirements that were inaccurately rumored to be part of the law. And these false provisions, as analyzed previously, were also the ones that people disliked most.

Where partisans appeared to most differ was not in their beliefs about the law, but instead in their evaluations of different provisions of the ACA. All 18 provisions that the survey measured were viewed more favorable by Democrats than by Republicans, regardless of whether the provisions were actually in the law (Table 4.9).

Table 4.9. *Evaluations of Provisions by Partisan Groups*

Provision	Evaluation – Mean (SD)		
	Republicans	Independents	Democrats
Provisions in the ACA	.10 (.60)	.31 (.59)	.51 (.51)
No dropped coverage	.64 (.50)	.71 (.47)	.81 (.37)
Make insurance for sale	.53 (52)	.64 (.46)	.78 (.39)
Subsidize seniors	.56 (.52)	.61 (.53)	.76 (.40)
Small business tax credits	.39 (.55)	.49 (.52)	.66 (.42)
Cover under 26	.27 (.64)	.50 (.59)	.71 (.46)
No capped coverage	.22 (.69)	.48 (.63)	.56 (.64)
No preexisting condition denial	.13 (.65)	.40 (.62)	.59 (.50)
Employers must provide	-.15 (.73)	.14 (.70)	.54 (.52)
Subsidize low income	-.14 (.66)	.11 (.65)	.41 (.58)
Drug companies fee	-.35 (.58)	-.03 (.62)	.19 (.56)
Insurance companies fee	-.41 (.56)	-.13 (.61)	.10 (.53)
Individual mandate	-.48 (.65)	-.22 (.73)	-.01 (.72)
Provisions NOT in the ACA	-.41 (.63)	-.30 (.65)	-.17 (.67)
Smoker fee	-.14 (.71)	-.07 (.73)	.02 (.69)
ID Card	-.25 (.73)	-.16 (.69)	-.08 (.67)
Soda tax	-.48 (.63)	-.27 (.69)	-.04 (.70)
Undocumented immigrants free	-.62 (.52)	-.36 (.63)	-.07 (.67)
Death panel	-.57 (.57)	-.45 (.61)	-.30 (.68)
Disclose illness to employers	-.39 (.64)	-.52 (.59)	-.53 (.61)
All provisions	-.07 (.61)	.10 (.61)	.28 (.56)

For the 12 provisions that were in the ACA, 11 received net positive evaluations from Democrats, with average ratings ranging from .10 to .81. Independent-identifying respondents gave net positive ratings to 9 out of the 12 provisions, while Republicans expressed support toward 7 out of the 12 provisions. It is worth noting that, however, even with these partisan differences, when we only consider the provisions that were actually in the ACA, Republicans still demonstrated a modest net positivity (M = .10, SD = .60). For the six provisions that were not in the ACA, evaluations were overwhelmingly negative across partisan groups, and Republicans remained most critical. Figure 4.1 provided a visualized summary of the level of informedness and provision evaluations by partisan groups.

As noted in Chapter 2, given the scope of this dissertation, I will not dive into exploring how or why evaluations of individual provisions vary across individuals and across partisan groups. However, it is worth pointing out a few variations in terms of the evaluations given to different provisions. For Republicans, for example, the provision that they disliked the most is the false claim that the ACA would require health care providers to treat undocumented immigrants for free (M = -.62, SD = .52), which was only considered marginally negative by Democrats (M = -.07, SD = .67). The most unpopular provision for both Democratic- and Independent-identifying respondents, namely that the ACA would require employees to reveal their medical histories to employers, was only ranked 5th on Republicans' most-disliked list. And for the provision that citizens would have to pay a fine if they do not have health insurance (i.e., the so-called "individual mandate"), it only received a marginally negative rating from Democrats, yet an overwhelmingly negative evaluation from Republicans.

These partisan differences in the evaluations of individual provisions of the ACA are not surprising. Indeed, the sentiments reflected in these contrasting evaluations are well aligned with differing values and ideologies that these respective partisan groups embrace. By focusing on the information processing mechanism underlying political attitude formation, this project does not at all deny the influences of partisan identity, as well as other political and social identities, on shaping political attitudes. On the contrary, the partisan differences revealed in both cognitive beliefs about and affective evaluations of the individual components of the ACA, as examined in this section, might interactively shape the overall attitude toward the law, which will be examined in Chapters 5 and 6.

Summary

This chapter provided a comprehensive review and descriptive analyses of the data. First, the high-quality data collected from a nationally representative sample ensures high levels of external validity and generalizability for the current project. Second, the MICE method imputing missing values offers a solid foundation for the ensuing Bayesian analyses (Graham, 2009; Schafer & Olsen, 1998). Third, echoing the discussion on belief certainty in Chapter 2 (Gross et al., 1995; Krosnick & Petty, 1995), the analysis of respondents' state of information on the components of the ACA further highlighted the importance of considering certainty as a separate dimension from accuracy to assess whether people truly hold the beliefs that they reported, which will potentially have a major impact on how corresponding beliefs are leveraged in the attitude formation process (Krosnick et al., 1993; Peterson, 2004). Lastly, both the cognitive and affective differences across partisan groups, as identified in differing beliefs about and evaluations of individual provisions of the ACA, are expected to contribute to the partisan attitudinal gap. With the theories, methods, and data presented in Chapters 2, 3, and 4 respectively, I now proceed to model the attitude formation process whereby individuals' beliefs about different provisions of the ACA, certainty associated with those beliefs, evaluations of different provisions, and their partisan identities, collectively shape their overall attitudes toward the law.

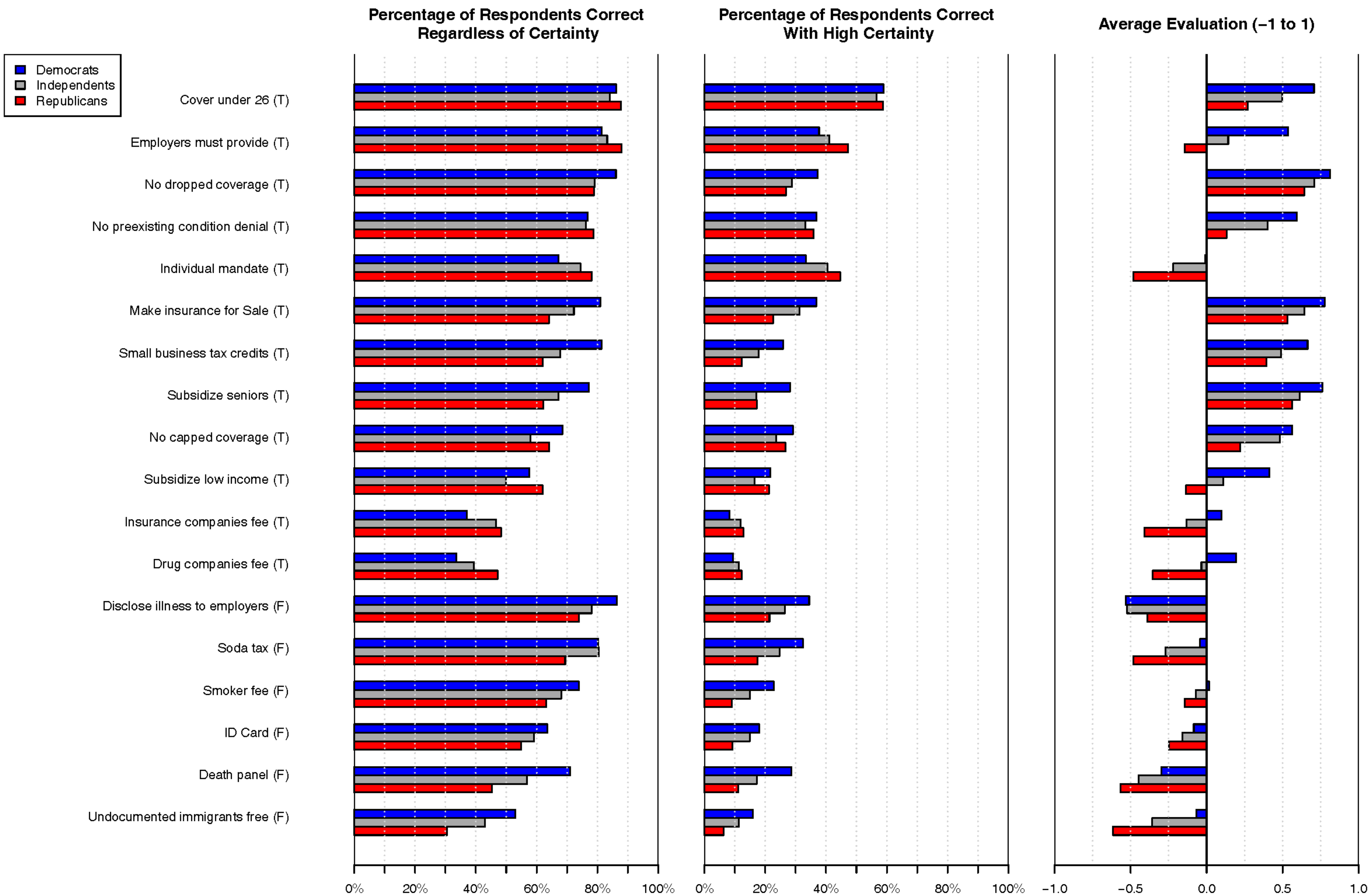

Figure 4.1 *Partisan Differences in Beliefs of and Evaluations about ACA Provisions*

CHAPTER 5

A Bayesian Estimation of the Belief-based Attitude Model

Following the theoretical model presented in Chapter 2, this chapter will test the proposition that individuals' overall attitudes toward an object are collectively shaped by their beliefs about different attributes of the object and their evaluations of each of those attributes, as articulated in the expectancy-value model of attitude (Fishbein, 1963; Fishbein & Azjen, 1975). It will also incorporate the level of certainty to which individuals hold their beliefs as an additional multiplicative variable to the original expectancy-value model of attitude (Gross et al., 1995; Krosnick et al., 1993; Peterson, 2004). Moreover, it considers that belief, belief certainty, and attribute evaluation across different attributes of the attitude object will have structurally similar relations with the overall attitude, while the unique effects of each of these variables associated with individual attributes are determined by the relative weight or importance of that attribute (van der Pligt & de Vries, 1998b; van Harreveld et al., 2000). It will also test whether those relations are maintained when the potential motivating factor of social identities—partisanship in particular—is accounted for.

More specifically, it asks: In terms of the overall attitude toward a particular political attitude object—the ACA, to what extent do (accurate and inaccurate) beliefs matter? Do the certainty with which those beliefs are held and the importance of those beliefs moderate the impact of beliefs on attitudes? Is the relation between beliefs and attitudes robust to partisanship? And does partisanship moderate the relations between beliefs and attitudes? Answers to these questions will collectively reveal 1) the sources of attitudes toward the ACA, and 2) the extent to which dis/misinformation correction is likely to influence individuals' judgments.

Model

As described in Chapter 4, respondents answered questions about 18 different provisions that a health care law that Congress passed in 2010 might do. 12 of these provisions are actual components of the ACA. The remaining six provisions are not in the law but widely circulated false claims about what the law will do.

For each provision, respondents were asked to indicate their belief about whether it is a part of the law, the certainty of that belief, and their evaluation of that provision. These three variables and their interaction terms will be weighted by the respective importance of each provision. The regression model is:

$$Attitude \sim \alpha + \sum_{i=1}^{18} \beta_i + \gamma + \sum_{m=1}^{7} \delta_m + \varepsilon$$

where α is the intercept/constant, β_i represents a vector of coefficients of all belief-related variables for 18 provisions, γ represents the influence of partisan identity, δ_m represents a vector of coefficients of all seven demographic covariates, and ε is the error term. And for each provision i:

$$\beta_i = \sum_{j=1}^{7} (\omega_i \cdot \tau_j)$$

where τ_{1-7} represent the effects of *belief* (b), *belief certainty* (c), *provision evaluation* (e), *belief* × *belief certainty* ($b \cdot c$), *belief* × *provision evaluation* ($b \cdot e$), *belief certainty* × *provision evaluation* ($c \cdot e$), and *belief* × *belief certainty* × *provision evaluation* ($b \cdot c \cdot e$) respectively, and ω_i represents the effect of the *importance* of each individual provision.

In practice, the effects of belief, belief certainty, provision evaluation, and their interaction terms for all 18 provisions will still be individually estimated (i.e., each β_i is comprised of seven $\lambda_{i,j}$). Seven parameters per provision will thus yield a total of 126 parameters to be estimated. However, these parameters are bounded by the structural relationships between τ_{1-7} and ω_i, such that $\lambda_{i,j} = \omega_i \cdot \tau_j$, as illustrated in Table 5.1.

Table 5.1 *Summary of Structural Constraints on the Relations between Belief-related Variables and Provision Importance*

Provision importance	Belief	Belief certainty	Provision evaluation	Belief × Belief certainty	Belief × Provision evaluation	Belief certainty × Provision evaluation	Belief × Belief certainty × Provision evaluation
(ω_i)	b (τ_1)	c (τ_2)	e (τ_3)	$b \cdot c$ (τ_4)	$b \cdot e$ (τ_5)	$c \cdot e$ (τ_6)	$b \cdot c \cdot e$ (τ_7)
Provision 1 (ω_1)	$\lambda_{1,1}$	$\lambda_{1,2}$	$\lambda_{1,3}$	$\lambda_{1,4}$	$\lambda_{1,5}$	$\lambda_{1,6}$	$\lambda_{1,7}$
Provision 2 (ω_2)	$\lambda_{2,1}$	$\lambda_{2,2}$	$\lambda_{2,3}$	$\lambda_{2,4}$	$\lambda_{2,5}$	$\lambda_{2,6}$	$\lambda_{2,7}$
…	…	…	…	…	…	…	…
Provision 18 (ω_{18})	$\lambda_{18,1}$	$\lambda_{18,2}$	$\lambda_{18,3}$	$\lambda_{18,4}$	$\lambda_{18,5}$	$\lambda_{18,6}$	$\lambda_{18,7}$

As explained in Chapter 3, this structure imposed on $\lambda_{i,j}$ is expected to regulate the relationship between the same variable associated with different provisions to tackle the problem of multicollinearity in traditional estimation methods. For example, it would be reasonable to expect that if an individual likes a provision more, she or he will tend to have a more favorable overall attitude as well. In contrast, it is unlikely that liking part of the law would lead to a more negative attitude toward the law overall. However, if the evaluations of Provision 1 and Provision 2 are highly correlated with one another, a situation might occur where the evaluation of Provision 1 is found positively associated with the overall attitude (a positive $\lambda_{1,3}$) while the evaluation of Provision 2 is found negatively associated with the overall attitude (a negative

$\lambda_{2,3}$), due to multicollinearity. This structural regulation imposed will dictate that $\lambda_{1,3}$ and $\lambda_{2,3}$ are both jointly determined by the importance of respective provisions (ω_1 and ω_2) and the general effect of provision evaluation (τ_3). By acknowledging the relationship between $\lambda_{1,3}$ and $\lambda_{2,3}$, and effectively incorporating it into the model, this method should lead to more stable, reliable, and accurate estimates of parameters. This structural regulation, $\lambda_{i,j} = \omega_i \cdot \tau_j$, is incorporated into the following Bayesian analyses as the first informative prior.

A second informative prior constraining the range of values for ω_i is specified to ensure the proposed structural regulation, $\lambda_{i,j} = \omega_i \cdot \tau_j$, can be properly computed. The constraint serves as a form of regularization, ensuring that the estimates of $\lambda_{i,j}$ do not become excessively large or unstable. As ω_i represents the relative importance of individual provisions, an informative prior distribution ranging from 0 to 1 is imposed, since it is reasonable to assume that the relative importance/weight that people attach to individual provisions will not be negative, which was discussed in Chapter 3, and the upper limit of 1 is simply a reference point as importance is always relative.

This model then allows us to thoroughly test whether the formation of individuals' expressed attitudes toward the ACA reflects a process of synthesizing their beliefs about different components of the law and their evaluations of those components. In particular, it is hypothesized that there would be a positive three-way interaction effect of *belief* × *belief certainty* × *provision evaluation* (τ_7) on the overall attitude toward the ACA. That is, if an individual believes that a provision is part of the ACA, holds this belief with high certainty, and evaluates this provision favorably, she or he will tend to express a more positive attitude toward the ACA.

At the same time, this model also allows the investigation of a perhaps less intuitive possibility that the overall attitude toward a public policy might be influenced by beliefs about what is not part of the policy. That is, individuals' overall attitudes toward the policy might be less favorable if they believe that a component that *should* be a part of the policy *is not* included. For example, if someone strongly favors the idea of an insulin price cap and thinks that it should be a part of any health care reform legislation, she or he might find it extremely disappointing that the ACA does not have such a provision, which might consequently lead to a less favorable attitude toward the law.[6]

This expectation would be manifested as a negative two-way interaction effect of *belief certainty* × *provision evaluation* (τ_6) on the overall attitude toward the ACA. Normally it would not be sensible to discuss a two-way interaction effect nested within a three-way interaction effect. However, since the variable *belief* is operationalized dichotomously (i.e., a provision is either believed to be part of the law [coded: 1] or not part of the law [0]), the two-way interaction effect of *belief certainty* × *provision evaluation* (τ_6) on the overall attitude is effectively assessing when someone believes that a particular provision is *not* in the law, how this belief, together with the certainty associated with that belief and the evaluation of the corresponding provision, might influence her or his overall attitude toward the ACA. And a negative τ_6 would indicate that if an individual believes that a provision is not part of the law, holds this belief with high certainty, but evaluates this provision favorably, she or he would tend to express a more negative overall attitude toward the ACA.

[6] The proposed insulin price cap has never become a part of the ACA. However, the Inflation Reduction Act of 2022 stipulated that, effective January 1, 2023, insulin copays would be capped at $35 per month for Americans who were covered by Medicare.

Analytical approach

The posterior probability distribution of the overall attitude toward the ACA (y) is modeled as a Gaussian distribution with a mean of μ and a standard deviation of ε. Two informative prior probability distributions of $\lambda_{i,j}$ and ω_i are incorporated into the model:

$$y \sim Normal(\mu, \varepsilon)$$

$$\mu = \alpha + \lambda_{i,j} \cdot x_{i,j} + \gamma \cdot p + \delta_m \cdot d_m$$

$$\lambda_{i,j} = \omega_i \cdot \tau_j$$

$$\omega_i \in [0, 1]$$

$x_{i,j}$ represents variable j of provision i, p represents partisanship, and d_m represents demographic covariate m. The Bayesian inference was then performed using RStan using the Hamiltonian Monte Carlo algorithm to calculate the posterior probability distributions of parameters. The RStan coding to materialize the regression model specified above is reported in Appendix I.

The analysis was then conducted by employing a computational procedure that involved generating posterior probability distributions for all the model parameters. This process entailed running a total of 55,000 iterations, with an initial 5,000 iterations being discarded to account for the burn-in phase. The burn-in phase is an essential step in an MCMC analysis as it helps ensure that the computations have successfully transitioned away from arbitrary initial values and have achieved proper convergence. In other words, the burn-in phase eliminates early iterations that may be biased by the choice of starting points. Increasing the number of burn-in iterations will thus result in more accurate estimations (Jang & Cohen, 2020).

The computational procedure was executed using four separate Markov Chains. By employing multiple chains, the analysis can benefit from increased robustness and a better assessment of convergence. For each Markov Chain, every 10th iteration was retained for inference purposes, effectively thinning the sampled iterations. Thinning is a technique used to reduce the autocorrelation between consecutive samples in the MCMC chain, which is essential in preventing overestimation of the precision of parameter estimates, which can occur if successive samples are highly correlated. By retaining only every 10th iteration, the analysis will achieve a more representative and independent set of samples from the posterior distribution, leading to improved inference quality (Jackman, 2009).

The combination of the four Markov Chains and the thinning process yielded a total of 20,000 samples that were drawn from the joint posterior probability distribution of the model parameters. These samples represent the combined outcome of the Bayesian analyses and serve as the basis for inferring the values and uncertainty of the model parameters.

It is essential to emphasize the importance of proper diagnostics and convergence assessment in Bayesian analysis employing MCMC methods. Convergence diagnostics help determine whether the Markov Chains have reached a stationary distribution and whether the generated samples can be considered reliable for drawing inferences. Several diagnostic tools can be employed for this purpose, such as trace plots, effective sample size (ESS), and R-hat (see McElreath, 2020). The use of multiple chains and the implementation of a burn-in phase are integral parts of the convergence assessment, as they provide additional safeguards against potential biases introduced by arbitrary initial values or poor mixing of the chains.

A trace plot is a graphical representation of the sampled values of a parameter across iterations in MCMC chains. By visually inspecting the trace plot, researchers can assess whether the chain has reached a stationary distribution. A well-mixed chain exhibits a random, “hairy caterpillar” pattern, with no apparent trends or drifts (Roy, 2020, p. 397). Poor mixing is indicated by trends, jumps, or long stretches in the trace plot, suggesting that the chain has not yet converged to the target distribution and additional iterations may be needed, or that the model specified is inherently flawed (Gelman et al., 2013; Nylander et al., 2008).

The effective sample size (ESS) is a measure of the number of independent samples obtained from the MCMC chain, taking into account the autocorrelation between successive samples (Robert & Casella, 2004). A high ESS indicates that the samples are relatively independent and provide a more reliable estimate of the posterior distribution. In contrast, a low ESS suggests that the samples are highly autocorrelated, leading to an overestimation of the precision of the parameter estimates (Kruschke, 2014).

The R-hat value, also known as the Gelman-Rubin diagnostic or potential scale reduction factor (PSRF), is a diagnostic tool that compares the within-chain and between-chain variances of multiple MCMC chains to assess convergence (Gelman & Rubin, 1992). An R-hat value close to 1 indicates that the chains have likely converged to the same target distribution, and the samples can be combined for inference. Values considerably different from 1 suggest that the chains have not yet converged, and additional iterations or modifications of the model may be necessary (Kruschke, 2014; McElreath, 2020).

The next section will offer a general assessment of the model convergence by inspecting the trace plots, ESS, and R-hat for major parameters in the model.

General model inspection

Figure 5.1 shows the trace plots illustrating the convergence of Markov Chains for estimating the intercept (α) and the effects of demographic covariates (δ_{1-7}). Figure 5.2 presents the trace plots demonstrating the patterns of iterations for estimating partisanship (γ) and all parameters for belief, belief certainty, attribute evaluation, and their interaction terms (τ_{1-7}).

Upon examining the trace plots generated from the Bayesian analysis, it appears that the separate Markov Chains generally demonstrated a satisfying level of convergence. Each chain, representing a unique set of starting values, meandered through the parameter spaces. Some of the parameters admittedly demonstrated greater variabilities (e.g., τ_5). But overall speaking, the chains coalesced as the iterations progressed, approaching an equilibrium state with overlapping trajectories. The general convergence of the chains was a testament to the effectiveness of the underlying sampling algorithm, which had successfully traversed the posterior probability distribution to reach regions of high probability density. The trace plots, serving as visual representations of these dynamic processes, revealed a comforting consistency across the chains and instilled confidence in the model.

The ESS and R-hat values are reported in Table 5.2. Across all parameters, the ESS statistics are larger than 18,000, and the R-hat values are consistently close to 1, both of which are convincing evidence for an adequate level of convergence. The ESS values are sufficiently large across all parameters, indicating a robust representation of the underlying distribution. The R-hat values hover close to the ideal value of 1, suggesting that the chains had converged well to the same stationary distribution. The convergence of the Markov Chains, as evidenced by the trace plots and the concurrence of ideal ESS and R-hat values, provides support for the reliability and stability of the Bayesian inferential processes, and bolsters the confidence in the model and its applicability to the problems at hand.

Due to their large quantities (18 ω_i and 126 $\lambda_{i,j}$, respectively), the trace plots, ESS values, and R-hat values for these parameters are not presented here but available in Appendix II. Visual examinations and closer inspections of the diagnostic statistics suggest that they also demonstrated satisfying converging tendencies.

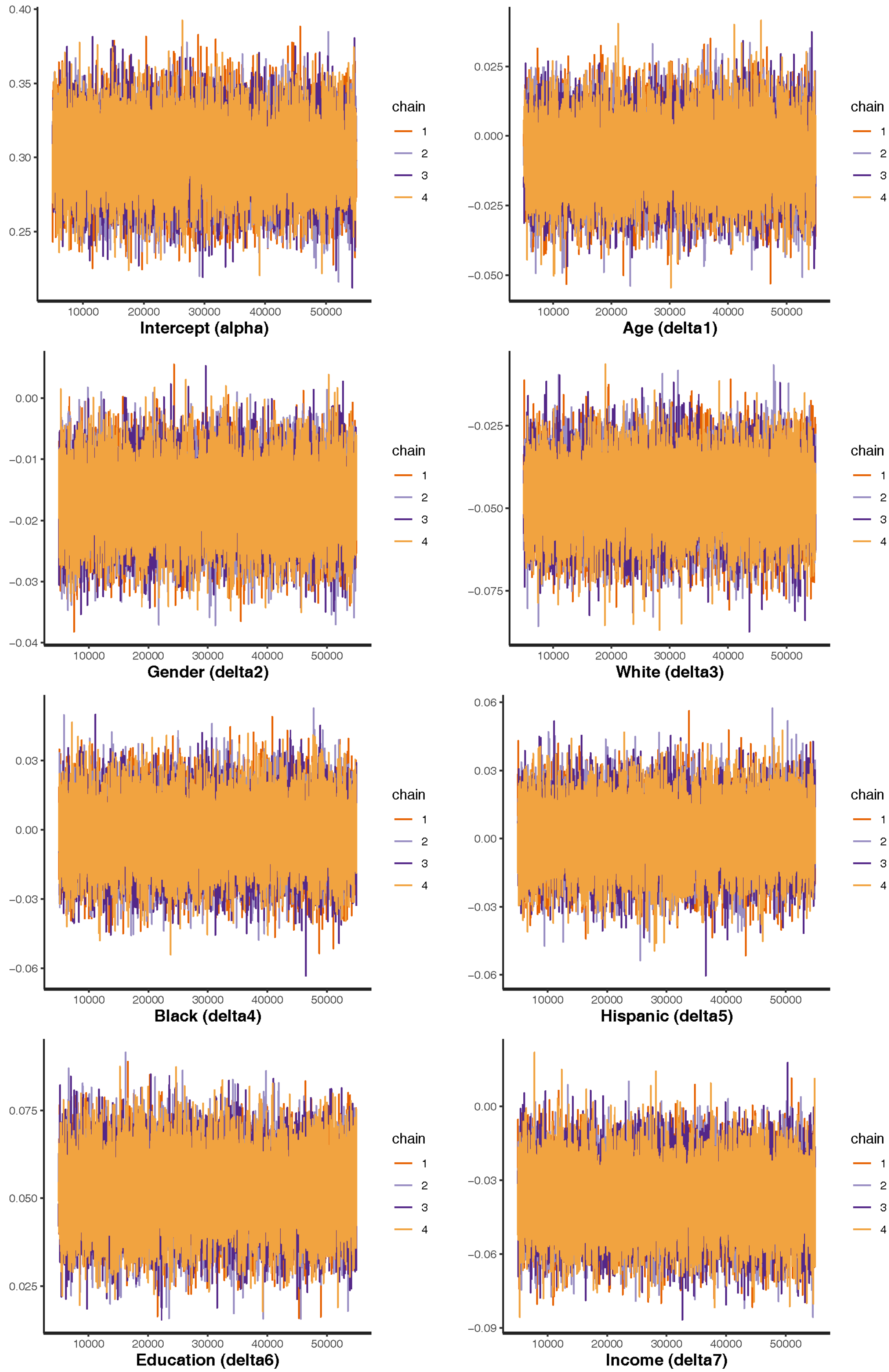

Figure 5.1 *Trace Plots for Intercept and Demographic Covariates*

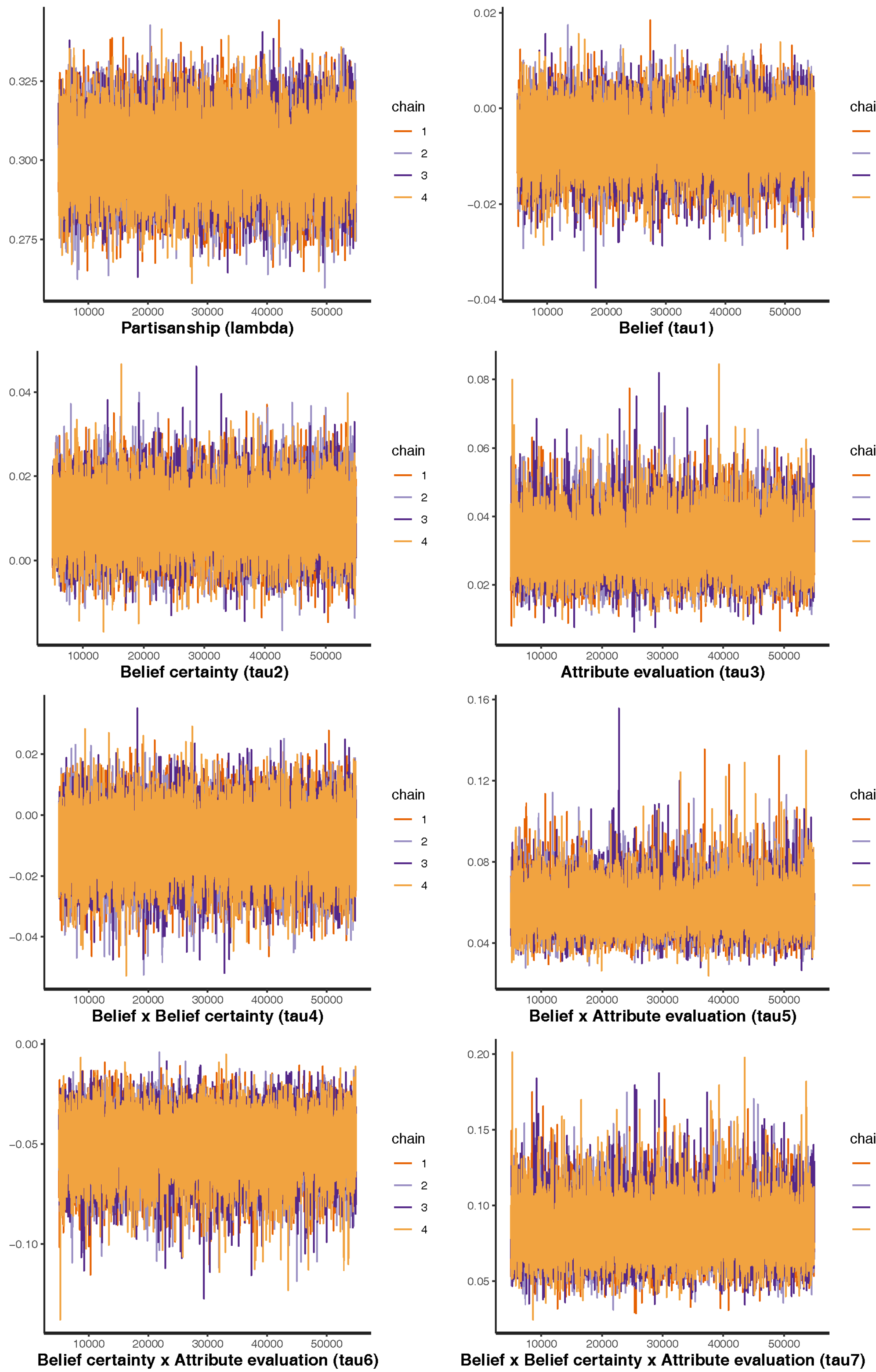

Figure 5.2 *Trace Plots for Partisanship and Belief-related Variables*

Table 5.2 *Model Diagnostic Statistics for Bayesian Inference*

	ESS	R-hat
Intercept (α)	19580	1.000
Age (δ_1)	20165	1.000
Gender (δ_2)	19799	1.000
White (δ_3)	20065	1.000
Black (δ_4)	19329	1.000
Hispanic (δ_5)	19693	1.000
Education (δ_6)	19858	1.000
Income (δ_7)	19701	1.000
Partisanship (γ)	19691	1.000
Belief (τ_1)	19424	1.000
Belief certainty (τ_2)	18326	1.000
Attribute evaluation (τ_3)	19677	1.000
Belief × Belief certainty (τ_4)	18249	1.000
Belief × Attribute evaluation (τ_5)	19078	1.001
Belief certainty × Attribute evaluation (τ_6)	19314	1.000
Belief × Belief certainty × Attribute evaluation (τ_7)	18770	1.000

Do beliefs matter?

With the diagnostics metrics showing convincing evidence for the model and the Bayesian inferences, I now proceed to present the results of the analysis. Table 5.3 summarizes the parameter estimates, which are the averaging effects based on the posterior probability distribution of the 20,000 samples. The mean value for each parameter shall be understood as how regression coefficients are normally interpreted, and the 95% HDI, as introduced in Chapter 3, is the Bayesian equivalent of 95% CI, where an interval that does not contain the value 0 indicates the equivalent of a "statistically significant" effect. [7]

[7] It is not entirely appropriate to discuss statistical significance in a Bayesian context. Frequentist statistics relies on the idea of repeated testing. In this framework, a null hypothesis is proposed, representing no effect or relationship between variables. A p-value is calculated, which represents the probability of obtaining the observed data or more extreme results, assuming the null hypothesis is true. The p-value is then compared to a predefined threshold, typically 0.05. If the p-value is below this threshold, the result is considered statistically significant, suggesting that it is unlikely the observed effect happened by chance alone.

On the other hand, Bayesian analysis is based on the concept of updating probabilities using Bayes' theorem. It combines prior beliefs about the parameters with the likelihood of the observed data to compute the posterior probability distribution of the parameters. Instead of making binary decisions about hypotheses, Bayesian analysis provides a continuous measure of evidence that can be used to update beliefs. The focus is on estimating the probability distribution of the parameter of interest and quantifying the uncertainty. Therefore, Bayesian analysis does not rely on p-values or the notion of statistical significance.

As can be seen in Table 5.3, in terms of demographics, women tended to favor the ACA more than men (δ_2 = -.017, 95% HDI [-.028, -.006]), and White respondents tended to express much more negative attitudes toward the ACA than respondents of other racial and ethnic groups (δ_3 = -.046, 95% HDI [-.067, -.026]). Respondents with a higher level of education tended to support the ACA more (δ_6 = .052, 95% HDI [.032, .072]), so did the respondents with lower income (δ_7 = -.037, 95% HDI [-.063, -.011]). And unsurprisingly, respondents' partisan identities had a major impact on their overall attitudes toward the ACA (γ = .302, 95% HDI [.280, .323]), such that Democrats expressed much more favorable attitudes toward the law than Republicans.

Table 5.3 *Bayesian Estimation of the Effects of Demographics, Partisanship, and Belief-related Variables on the Overall Attitudes Toward the ACA*

	Mean	95% HDI
Intercept (α)	.301	[.256, .346]
Age (δ_1)	-.007	[-.031, .016]
Gender (δ_2)	-.017	[-.028, -.006]
White (δ_3)	-.046	[-.066, -.026]
Black (δ_4)	-.002	[-.029, .025]
Hispanic (δ_5)	.002	[-.025, .028]
Education (δ_6)	.052	[.032, .072]
Income (δ_7)	-.037	[-.063, -.011]
Partisanship (γ)	.302	[.280, .323]
Belief (τ_1)	-.007	[-.018, .005]
Belief certainty (τ_2)	.010	[-.004, .024]
Provision evaluation (τ_3)	.032	[.018, .048]
Belief × Belief certainty (τ_4)	-.009	[-.029, .011]
Belief × Provision evaluation (τ_5)	.058	[.040, 081]
Belief certainty × Provision evaluation (τ_6)	-.050	[-.080, -.026]
Belief × Belief certainty × Provision evaluation (τ_7)	.084	[.053, .122]

In terms of the core variables in the belief-based attitude model that the current project focuses on, there is no discernable effect for either *belief* (τ_1) or *belief certainty* (τ_2) observed in the posterior probability distribution, suggesting that neither simply believing a provision is part of the ACA with no certainty nor the presence of certainty alone for an item that a respondent did not believe is in the law would change individuals' overall attitudes toward the law.

However, there is a clear effect of *provision evaluation* (τ_3 = .032, 95% HDI [.018, .048]), suggesting that liking a potential component of the ACA is positively associated with the law's overall favorability when the individual does not believe the item is in the law but is uncertain about this fact. At the same time, there was a negative two-way interaction effect of *belief certainty* × *provision evaluation* on the overall attitude (τ_6 = -.050, 95% HDI [-.080, -.026]), which effectively indicates that liking a potential component of the ACA is negatively associated with the law's overall favorability when the individual does not believe this provision is in the law and is sure about this fact. Therefore, when individuals confidently hold the belief that a certain provision is *not* part of the ACA while evaluating this provision favorably, their overall attitudes toward the ACA tended to be more negative, which supported the expectation that individuals' overall attitude toward an object might be related to what was not considered as a part of that object.

The analysis also revealed a positive two-way interaction effect of *belief* × *provision evaluation* ($\tau_5 = .058$, 95% HDI [.040, .081]), suggesting that liking a provision of the ACA that someone believes is in the law is positively associated with the overall attitude, even if this belief is held with no certainty. A belief held with full certainty, on the contrary, appears to have a greater impact. As expected, a positive three-way interaction effect of *belief* × *belief certainty* × *provision evaluation* on the overall attitude was found ($\tau_7 = .084$, 95% HDI [.053, .122]), which further supported the expectation of the regulatory role of belief certainty in the belief-based model of political attitude formation. The influence of favoring or opposing a particular provision was evident when individuals were confident about their beliefs.

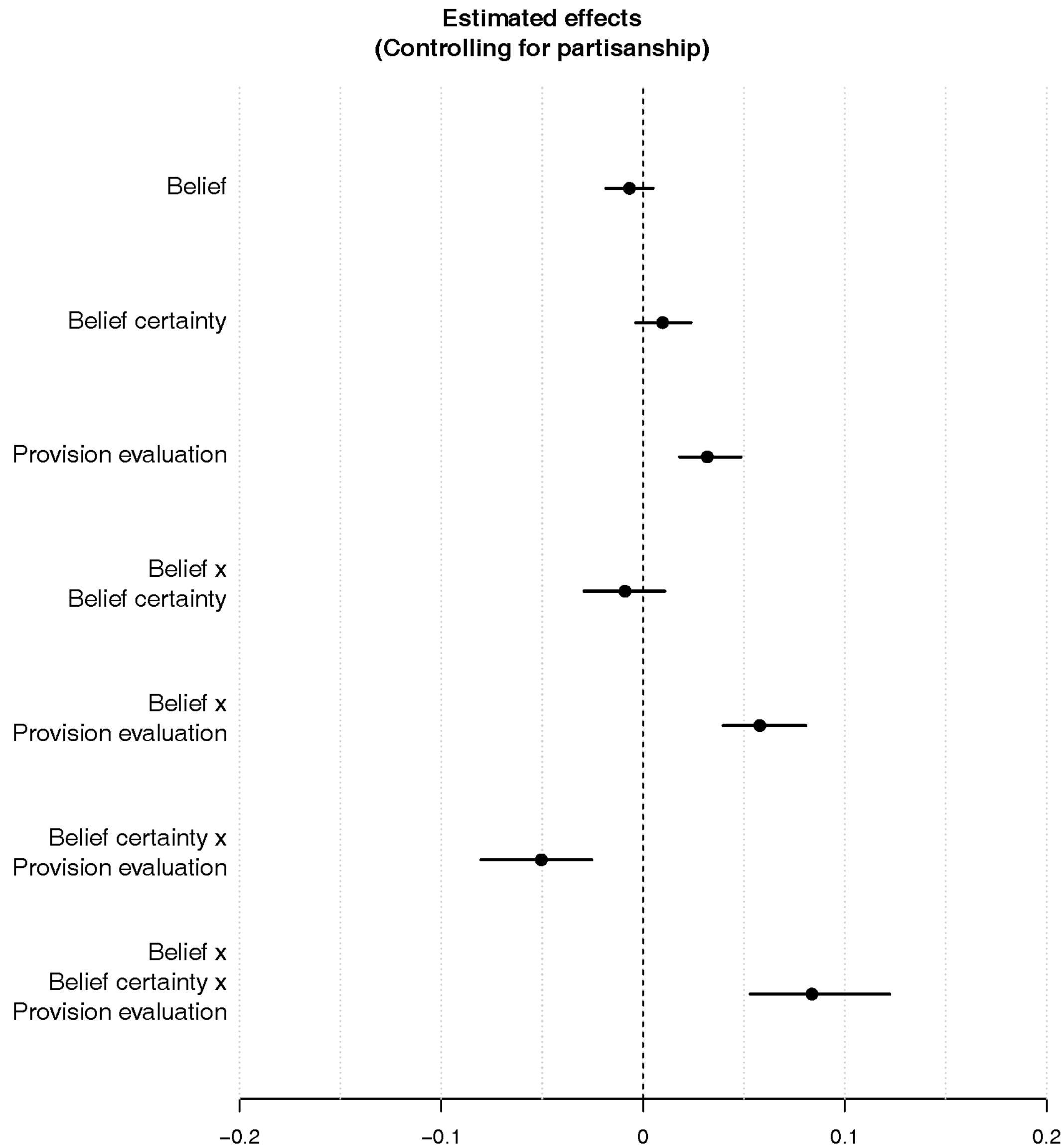

Figure 5.3 *Bayesian Estimation of the Effects of Belief-related Variables on the Overall Attitudes Toward the ACA*

The Bayesian model also allows the computations of the relative importance of individual provisions (ω_i), which are presented in Figure 5.4. The provisions in the figure were ranked by their respective importance rating. The letter T or F after the provision's name denotes whether the provision was actually in the ACA or not.

Overall, the provision that citizens will have to pay a fine if they do not have health insurance is deemed as the most important provision, though the posterior probability distribution of its importance rating did overlap with the untrue statement that the ACA would require health care providers to treat undocumented immigrants for free. On the other end of the spectrum, the false claims that the ACA would require fast food restaurants selling unhealthy food or drinks to pay a fee to the federal government and that the ACA would require every American to show a government health care identification card in order to get medical care at a hospital were deemed least important, though there are no meaningful differences between their importance ratings and some other provisions such as disclosing illness to employers or subsidizing senior citizens with high prescription drug costs. The full parameter estimates of the importance ratings are available in Appendix III.

Do partisans differ?

The analyses conducted so far have shown that a belief-based attitude model is warranted. Despite the indisputable effect of partisanship on people's overall attitudes over this highly partisan issue, individuals' beliefs about what constitutes the ACA, the certainty to which they hold those beliefs, and their evaluations of the components of the ACA, were found to be jointly related to their overall attitudes toward the law.

Since one of the critical issues that the current project aims to address is whether political attitudes could at least be partly attributed to information and beliefs that individuals hold or are largely shaped by their political identities, the next question would naturally be: Does the belief-based model established in the analyses above hold across the board? In other words, is the relation between belief (as well as belief certainty and provision evaluation) and attitude robust to partisanship?

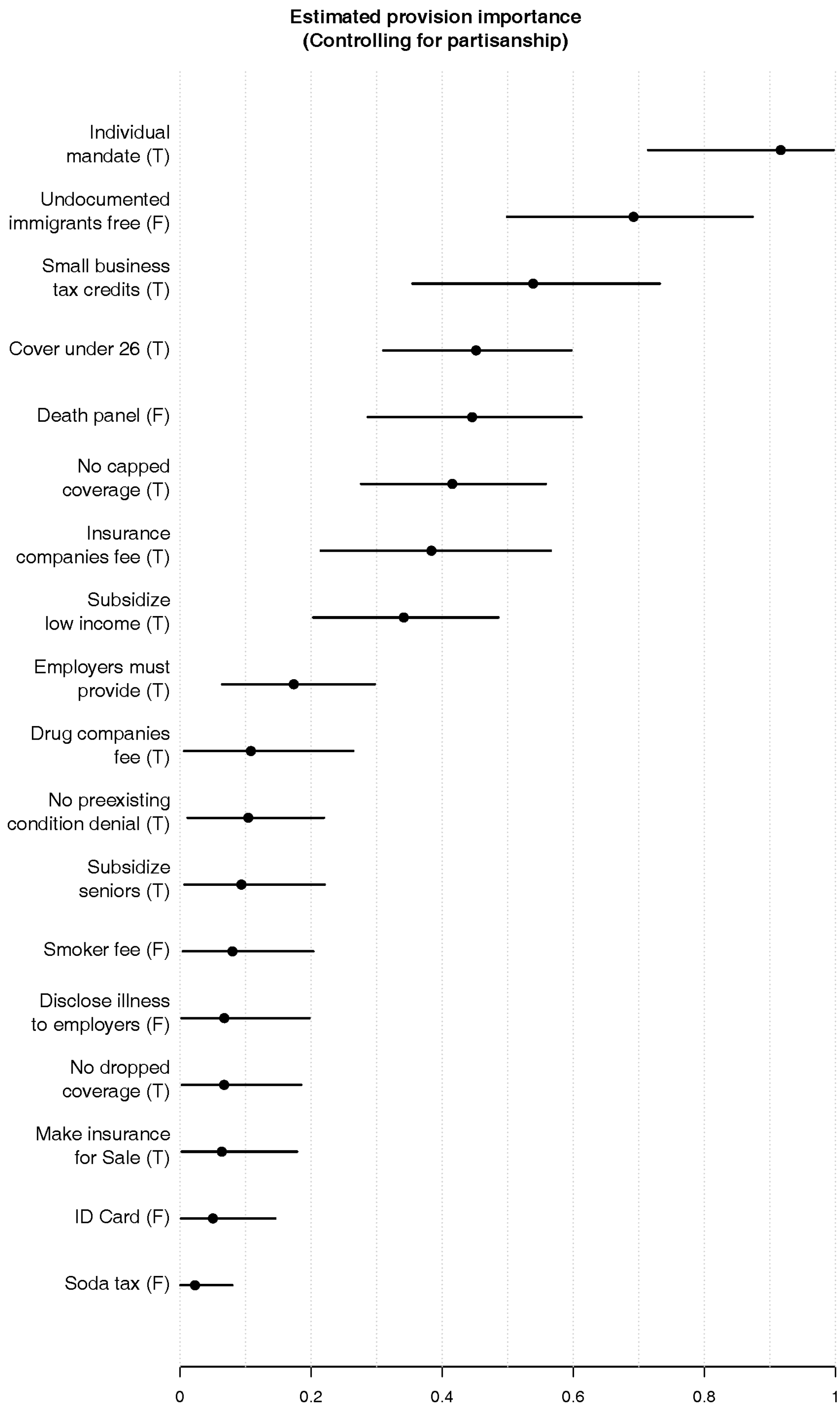

Figure 5.4 *Bayesian Estimation of Provision Importance*

To examine whether there exist partisan differences in how informational beliefs influence individuals' overall attitudes toward the ACA, three separate Bayesian analyses were performed with Republican-, Independent-, and Democratic-identifying respondents respectively. The model specification remains the same with the only exception that γ, which represents partisan identity in the original model, was removed. The RStan coding is reported in Appendix IV.

The computations were conducted in the same manner as reported above, with the first 5,000 iterations as the burn-in phase followed by 50,000 iterations for sampling posterior probability distributions. The algorithm was run on four Markov Chains with every 10th iteration retained for inference, yielding a total of 20,000 samples for each analysis. All three models converged well, and the model convergence diagnostics are available in Appendix V.

The results of all three analyses are reported in Table 5.4. The three-way interaction effect of *belief* × *belief certainty* × *provision evaluation* on the overall attitude (τ_7) remains positive for all three partisan groups, with 95% HDIs greater than zero, which suggests that the mechanism that belief, belief certainty, and provision evaluation collectively shaped overall attitudes toward the ACA operates in a similar manner for all respondents regardless of their partisan identities. The pattern is more clearly illustrated in Figure 5.5. Individuals holding a belief that a provision is a part of the ACA with certainty while evaluating this provision positively tended to express a more favorable overall attitude toward the law. The pattern remains valid for respondents of all partisan groups. It can therefore be confidently concluded that the belief-based model of attitude that the current project proposed is robust to the influence of partisanship, even in the context of an extremely partisan issue.

At the same time, it is worth noting that the two-way interaction effect of *belief certainty* × *provision evaluation* on the overall attitude (τ_6) remains negative for Republicans and Independents, but not for Democrats. That is, Republican- and Independent-identifying respondents tended to express less favorable overall attitudes towards the ACA when they were certain that a provision was not encompassed within the ACA yet evaluated this provision positively. This pattern, however, was not observed among Democrat-identifying respondents. Democrats did not perceive the ACA as less favorable, even when they believe that something they like is not in it. Conversely, for both Republicans and Independents, a confidently held belief that a favored provision was not incorporated as part of the ACA resulted in a diminished overall appreciation for the law.

The computation also revealed that the importance ratings of individual provisions (ω_i) given by members of different partisan groups had different patterns across provisions. As illustrated in Figure 5.6, some of the provisions were consistently evaluated as more important by respondents of all partisan groups (e.g., fine for uninsured), while some other provisions were consistently considered less important (e.g., soda tax). However, there are provisions for which the importance ratings considerably diverged among respondents with different partisan identities. For example, the stipulation to subsidize low-income citizens to pay for health insurance is a concern much more important to Republicans than to Democrats and Independents, yet the provision preventing insurance companies from limiting coverage was considered more important by Democrats than by Independents and Republicans. The full parameter estimates of the importance ratings are available in Appendix VI.

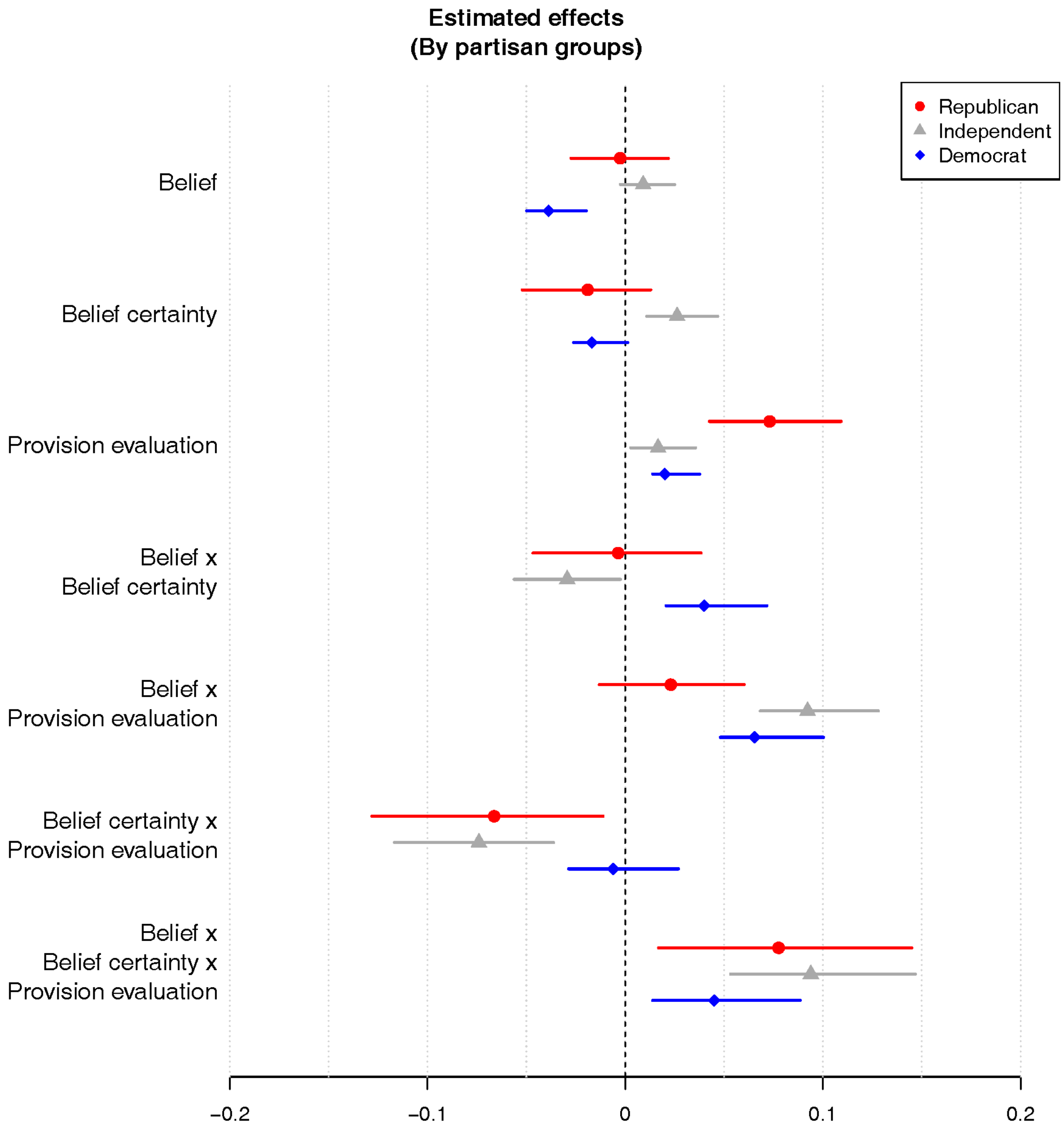

Figure 5.5 *Bayesian Estimation of the Effects of Belief-related Variables on the Overall Attitudes Toward the ACA by Partisan Groups*

Table 5.4 *Bayesian Estimation of the Effects of Demographics and Belief-related Variables on the Overall Attitudes Toward the ACA by Partisan Groups*

	Republicans		Independents		Democrats	
	Mean	95% HDI	Mean	95% HDI	Mean	95% HDI
Intercept (α)	.402	[.305, .504]	.419	[.355, .484]	.612	[.533, .690]
Age (δ_1)	.018	[-.024, .060]	-.051	[-.088, -.014]	-.006	[-.048, .036]
Gender (δ_2)	.001	[-.019, .020]	.008	[-.010, .025]	-.077	[-.097, -.057]
White (δ_3)	-.100	[-.141, -.059]	-.026	[-.056, .005]	-.088	[-.123, -.052]
Black (δ_4)	.526	[.337, .715]	.105	[.059, .151]	-.024	[-.064, .016]
Hispanic (δ_5)	-.015	[-.071, .040]	.052	[.012, .093]	-.073	[-.117, -.029
Education (δ_6)	.139	[.103, .175]	-.022	[-.053, .009]	.066	[.030, .103]
Income (δ_7)	-.060	[-.109, -.011]	-.054	[-.096, -.012]	.013	[-.034, .061]
Belief (τ_1)	-.003	[-.027, .022]	.009	[-.005, .025]	-.039	[-.060, -.020]
Belief certainty (τ_2)	-.019	[-.052, .013]	.026	[.009, .047]	-.017	[-.036, .001]
Provision evaluation (τ_3)	.073	[.043, .111]	.017	[.002, .036]	.020	[.004, .038]
Belief × Belief certainty (τ_4)	-.003	[-.047, .038]	-.029	[-.059, -.002]	.040	[.010, .072]
Belief × Provision evaluation (τ_5)	.023	[-.013, .060]	.092	[.066, .129]	.065	[.038, .099]
Belief certainty × Provision evaluation (τ_6)	-.066	[-.128, -.011]	-.074	[-.120, -.037]	-.006	[-.039, .026]
Belief × Belief certainty × Provision evaluation (τ_7)	.078	[.017, .145]	.094	[.050, .146]	.045	[.004, .090]

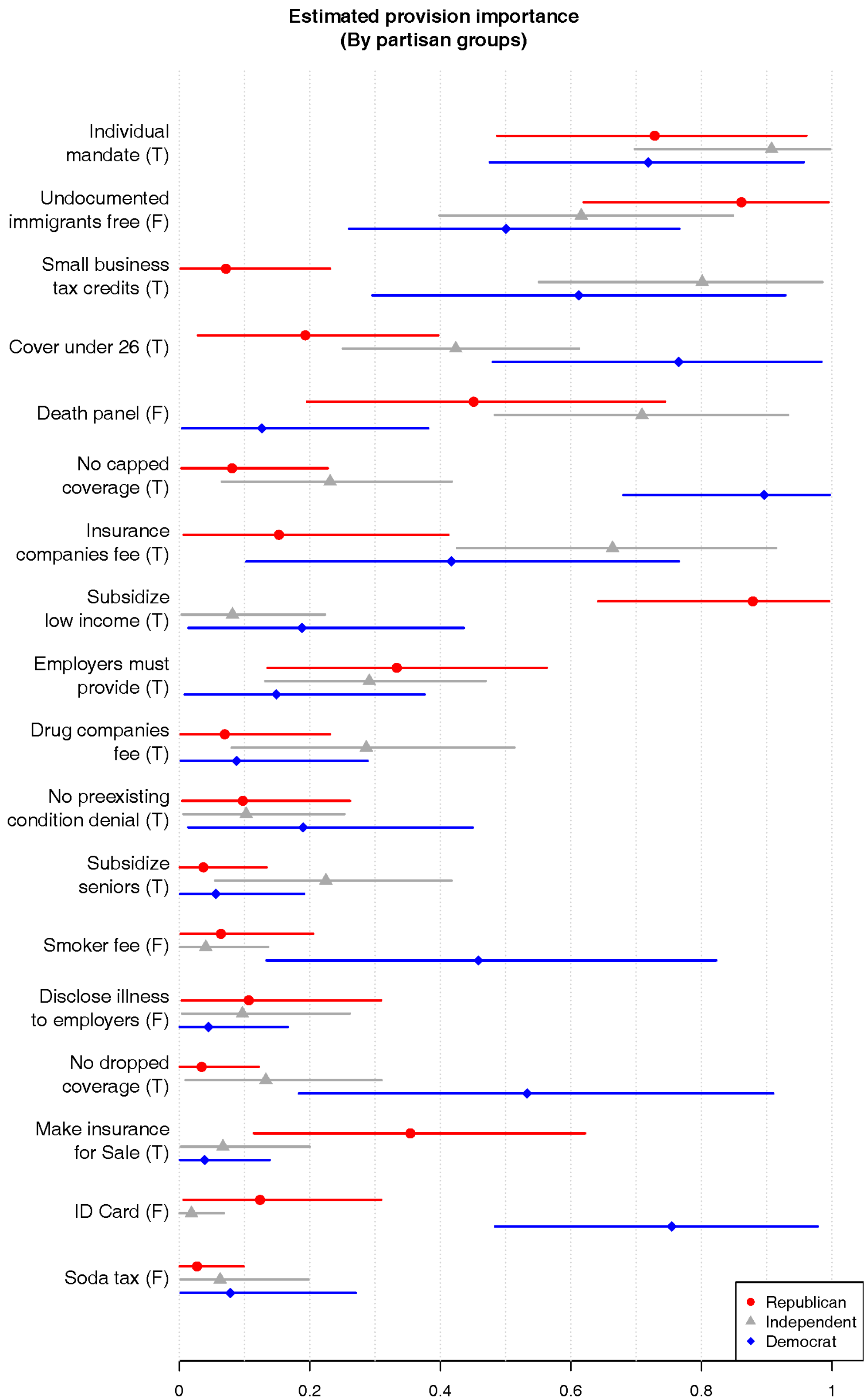

Figure 5.6 *Bayesian Estimation of Provision Importance by Partisan Groups*

Summary

Leveraging Bayesian techniques with MCMC algorithms, this chapter investigated how individuals' overall attitudes toward a complex object might be related to their informational beliefs about different components of the object, the level of certainty associated with those beliefs, and their evaluations of those components. Inspections of the trace plots and diagnostic statistics of the proposed Bayesian model showed compelling evidence for the convergence of separate Markov Chains in the computation and estimation processes, lending confidence in the reliability of parameter estimates and the overall validity of the model. The notion that different informational beliefs about and evaluations of various attributes or components of an attitude object will have structurally similar relations with the overall attitude is well supported.

The results substantiated the conjecture that to have a more favorable attitude toward the ACA, it helps to hold a belief that a provision that she or he likes is part of the law with certainty, and this mechanism holds for respondents across partisan groups. At the same time, one might express a more negative attitude toward the ACA if they confidently believe that a provision favored by them is not part of the law, yet this pattern only remains valid for Republicans and Independents but not for Democrats.

Despite the profound effect of partisan identities, the analyses in this chapter provided convincing evidence for a belief-based attitude model, that the joint influence of belief, belief certainty, and provision evaluation on the overall attitude toward the ACA is robust to the impact of partisanship. Furthermore, it highlighted the importance of belief certainty in understanding how information might shape people's attitudes— a confidently held belief could exert meaningful influences in the attitude formation process. With the belief-based model with Bayesian inference being established and the role of belief certainty assured, I now proceed to examine how the corrections of misbeliefs and the increases in belief certainties might change individuals' attitudes. Based on the model parameters obtained from the Bayesian analyses, I will perform a series of counterfactual simulations to show what would happen if people were better-informed about the ACA and were more certain about their beliefs.

CHAPTER 6

A (Hypothetical) Better-informed Public

Chapter 5 validates a belief-based model of attitudes using Bayesian inference. More specifically, individuals' overall attitudes toward the ACA are at least in part attributable to their beliefs about what constitutes the law and their evaluations of those constituent parts. The central role of informational belief in the formation of individuals' attitudes naturally leads to the next question: What would public opinion on the ACA look like if citizens knew more about the law? As discussed in Chapter 1, a tremendous amount of dis/misinformation about the ACA was circulated in media coverage, political debates, and public discussion throughout the legislation process. And as revealed in Chapter 4, many Americans mistakenly believed that a set of negatively valanced provisions were part of the law, and correct beliefs about the law held with great certainty were even rarer. Given that these beliefs appear to be a critical source of people's ultimate attitudes toward the ACA, as established in Chapter 5, it stands to reason that changes in beliefs (as well as in belief certainties) might induce corresponding changes in people's attitude toward the law. Gauging attitudinal changes ensued from belief changes could help ascertain the impact of information in the attitude formation process.

Different from most past experimental studies using an intervention approach to provide participants with one new piece of correct information at a time and assess whether there is an attitudinal change after the information intervention (e.g., Grigorieff et al., 2020; Ranney & Clark, 2016), this project adopts a different approach—statistical simulation—to holistically assess how changing multiple beliefs (as well as corresponding belief certainties) simultaneously would have a collective impact on people's attitudes, by simulating a series of counterfactual scenarios where people are better-informed about the ACA with greater certainty.

Counterfactual simulations

The counterfactual simulation method, though admittedly less common than the information intervention approach, remains a valid, well-recognized, and suitable technique to investigate the potential impact of changes in beliefs and information. A number of prior studies have done this by estimating a general measure of informedness or knowledgeability, and then generating predicted values or probabilities of various outcomes for the entire population when the observed level of informedness was replaced with a different, usually higher level of informedness (e.g., Althaus, 1998; Bartels, 1996; Fowler & Margolis, 2014; Gilens, 2001; Hansen, 2009; Lau & Redlawsk, 1997; Li & Pasek, 2022; Toka, 2008).

Counterfactual simulations, as used in these studies, involve creating hypothetical scenarios where individuals are assumed to possess different levels of information, knowledge, or awareness than they actually do. The primary objective is to understand how these changes in information levels could potentially affect individuals' attitudes and behaviors. By simulating a situation where people are better-informed or even fully informed, researchers can isolate the effects of information on the variables of interest, such as policy preferences or voting choices. This approach enables them to identify the potential consequences of different states or environments of information and investigate the extent to which disparities in information may impact political outcomes.

Similar to its information intervention counterparts, counterfactual simulations could isolate the effects of information on the variables of interest by creating hypothetical scenarios where information level is the only variable being changed, therefore controlling for other potentially confounding factors (Althaus, 1998; Bartels, 1996).

Different from experimental methods, counterfactual simulations can be applied to various data sources, such as observational data or survey data, allowing researchers to study a wide range of scenarios and contexts. Its flexibility in handling different sources of data lends itself to greater ecological validity and helps eliminate the possibility of experimenter demand effects influencing the outcomes. It can thus serve as the basis for interventions and possible policy changes in real life by providing researchers, educators, and policymakers with valuable insights into the possible consequences of different communication strategies (Hansen, 2009; Toka, 2008).

Most importantly, in the context of the current study, counterfactual simulations allow changing multiple pieces of beliefs, corresponding belief certainties, and even provision evaluations simultaneously, and testing their collective impact on the overall attitude. By building a simulation based on the belief-based model of attitude established in Chapter 5, we can estimate what would happen if Americans had known more about different components of the law, which ostensibly should influence their attitudes.

Models

I employed two different sets of models—linear regression and binomial logistic regressions respectively—to predict individuals' attitudes toward the ACA under various counterfactual scenarios.

Linear regression model

The first set of counterfactual simulations is based on the Bayesian linear regression model used in Chapter 5:

$$y \sim Normal(\mu, \varepsilon)$$

$$\mu = \alpha + \lambda_{i,j} \cdot x_{i,j} + \gamma \cdot p + \delta_m \cdot d_m$$

$$\lambda_{i,j} = \omega_i \cdot \tau_j$$

$$\omega_i \in [0, 1]$$

Through the inferences performed in Chapter 5, all the parameters in these equations were computed, representing the average effects of individual variables, based on data directly collected from respondents. That is, the values of $\lambda_{i,j}$ (for variable j of provision i), γ (for partisanship), and δ_m (for demographic covariate m) are available. The equations can then be rewritten with these parameter estimates, to make counterfactual predictions about individuals' attitudes toward the ACA ($\tilde{y}$), with the counterfactual sets of provision-related variables ($\tilde{x}_{i,j}$), and the original partisanship and demographic variables (p and d_m):

$$E(\tilde{y}|\tilde{x}_{i,j}, p, d_m) \sim Normal(\mu, \varepsilon)$$

$$\mu = \alpha + \lambda_{i,j} \cdot \tilde{x}_{i,j} + \gamma \cdot p + \delta_m \cdot d_m$$

The single most critical difference in terms of modeling between the counterfactual simulation and the Bayesian analyses performed in Chapter 5 is that the predicted overall attitude ($\tilde{y}$) is not part of the known data. Instead, it is now an unknown parameter to be estimated for every individual based on a new set of counterfactual data ($\tilde{x}_{i,j}$), using the parameter estimates generated from previous Bayesian inferences based on the observed data. The RStan coding to materialize this simulation is reported in Appendix VII.

The simulations then consider three hypothetical scenarios (i.e., three different sets of $\tilde{x}_{i,j}$). In the first counterfactual scenario (*All Correct*), respondents possess correct beliefs with their original level of certainty associated with corresponding beliefs. That is, all 12 provisions that are in the ACA are correctly identified as in the law, all 6 provisions that are rumored to be part of the ACA but actually not are correctly identified as not in the law, and their reported certainty level with regard to each of those beliefs is retained. In practice, it means that, for each provision i, $\tilde{x}_{i,1}$ (belief) and all interaction terms involving belief ($\tilde{x}_{i,4}$, $\tilde{x}_{i,5}$, and $\tilde{x}_{i,7}$) are now amended to reflect correct beliefs, while $\tilde{x}_{i,2}$ (belief certainty), $\tilde{x}_{i,3}$ (provision evaluation), and $\tilde{x}_{i,6}$ (belief certainty × provision evaluation) remain the same as observed data.

The second counterfactual scenario (*Fully Certain*) considers a different situation where respondents hold their original beliefs but have complete confidence in their beliefs. For each provision i, belief certainty ($\tilde{x}_{i,2}$) and all interaction terms concerning belief certainty ($\tilde{x}_{i,4}$, $\tilde{x}_{i,6}$, and $\tilde{x}_{i,7}$) will be amended to reflect a full certainty, while other variables remain unchanged.

In the third scenario (*Optimal*), individuals are set to hold all beliefs correctly with a full level of certainty, and their original evaluations of individual provisions remain the same as observed data. These three counterfactual simulations will then be compared to the *Baseline* scenario, where the original beliefs, belief certainties, and provision evaluations as reported by the respondents were used to predict attitudes. These analyses could therefore allow estimating the potential effects of changes in belief, belief certainty, and a combination of belief and belief certainty, on individuals' attitudes toward the ACA.

Sequential logistic regression models

The second set of models takes a different approach. Instead of seeing attitude as an interval variable and estimating it with a linear regression analysis, it attempts to make predictions about attitude as how it was operationalized in the survey (i.e., an ordinal measure with five response options ranging from "strongly oppose" to "strongly favor"), which has the potential to present a clearer and more nuanced picture of the effects of belief and belief certainty on attitudes because it can show the distribution of the predicted attitudes when people have different states of information about the components of the ACA.

To achieve this goal, I performed four separate binomial logistic regression analyses to assess how belief, belief certainty, provision evaluations, and their interaction terms related to the overall attitude toward the ACA (y_n). In each of these analyses, the overall attitude toward the ACA (y_n) is not treated as a numerical value on a 0-to-1 scale, as how it was processed in the linear regression analysis. Instead, it was operationalized as a binary outcome variable. Table 6.1 summarizes how y_n was specified in the four separate estimations.

Table 6.1 *Specifications of Predicted Attitude for Logistic Regression Models*

Outcome variable	Specifications
y_1	"Strongly oppose" as 1; others as 0
y_2	"Strongly oppose" and "oppose" as 1; others as 0
y_3	"Strongly oppose," "Oppose," and "Neither favor nor oppose" as 1; others as 0
y_4	"Strongly oppose," "Oppose," "Neither favor nor oppose," and "Favor" as 1; "Strongly favor" as 0

Since the overall attitude is now a binary outcome variable, it was then modeled with a Bernoulli distribution rather than a Gaussian distribution in the linear regression analysis, and the same independent variables in the linear regression model were used as predictors:

$$y_n \sim Bernoulli(\alpha + \lambda_{i,j} \cdot x_{i,j} + \gamma \cdot p + \delta_m \cdot d_m)$$

$$\lambda_{i,j} = \omega_i \cdot \tau_j$$

$$\omega_i \in [0, 1]$$

The four separate analyses would then generate four different sets of parameter estimates, depending on which version of y_n was being estimated. Four separate equations can then be written with these four different sets of parameter estimates, to make predictions about whether an individual's attitude toward the ACA ($\tilde{y}_n$) falling in one category (1) or the other (0), in one specific estimation (predicting $\tilde{y}_1$, $\tilde{y}_2$, $\tilde{y}_3$, or $\tilde{y}_4$), given a specific counterfactual scenario:

$$E(\tilde{y}_n|\tilde{x}_{i,j}, p, d_m) \sim Bernoulli(\alpha + \lambda_{i,j} \cdot \tilde{x}_{i,j} + \gamma \cdot p + \delta_m \cdot d_m)$$

Similar to counterfactual simulations using the linear regression model, the predicted overall attitude ($\tilde{y}_n$) in logistic counterfactual simulations is not part of the known data but an unknown parameter to be estimated for every individual based on a set of counterfactual data ($\tilde{x}_{i,j}$), using the parameter estimates generated from previous Bayesian logistic regression inferences based on observed data. The RStan coding is available in Appendix VIII.

The same three sets of counterfactual data ($\tilde{x}_{i,j}$) that were used in the linear regression models were then fed to the logistic regression models to make predictions. Therefore, for the logistic regression models, there were also three different sets of counterfactual simulations, and within each simulation, four separate logistic regression analyses were performed to compute the predicted probability of one's expressed attitude. Table 6.2 provided an overall summary of the models and scenarios:

Table 6.2 *Summary of Counterfactual Scenarios and Analytical Models*

Model / Scenario	Linear regression (Model 1)	Logistic regression (Model 2)
Baseline: Original belief, original certainty	$E(\tilde{y}\|\tilde{x}_{i,j}, p, d_m) \sim Normal(\alpha + \lambda_{i,j} \cdot \tilde{x}_{i,j} + \gamma \cdot p + \delta_m \cdot d_m, \varepsilon)$	$E(\tilde{y}_n\|\tilde{x}_{ij}, p, d_m) \sim Bernoulli(\alpha + \lambda_{ij} \cdot \tilde{x}_{i,j} + \gamma \cdot p + \delta_m \cdot d_m)$
All Correct: Correct belief, original certainty		
Fully Certain: Original belief, full certainty	One predicted attitude ($\tilde{y}$) is generated for each individual in each scenario	Four predicted attitudes ($\tilde{y}_n$) are generated for each individual in each scenario
Optimal: Correct belief, full certainty		

Methods

The technical details of these counterfactual simulations are the same as the Bayesian inferences conducted in Chapter 5. The posterior probability distributions of all parameters were computed through 55,000 iterations, discarding the first 5,000 iterations as burn-in phase, which is to ensure model convergence. The algorithm was run on four separate Markov Chains with every 10^{th} iteration retained for inference, yielding 20,000 samples from the joint posterior probability distribution of the model parameters.

In the counterfactual simulations using linear regression analysis (Model 1), for every single individual, there will be 20,000 predicted attitudes ($\tilde{y}$) generated, and the average value of these 20,000 $\tilde{y}$ is the mean predicted attitude toward the ACA for that individual.

In the counterfactual simulations using logistic regression analysis (Model 2), for each individual estimation (out of four, depending on how the outcome variable is coded), there will again be 20,000 predicted attitudes ($\tilde{y}_n$) generated for each respondent. The total number of "1" divided by 20,000 will be the predicted probability that the individual's attitude falls into the response category coded as "1". That is, out of the 20,000 iterations, if a respondent's attitude was predicted to be "1" for 18,000 times and to be "0" for 2,000 times, she or he has a 90% probability (18,000/20,000) to express the attitude coded as "1", given a specific counterfactual scenario. And the average predicted probability for all individuals in one estimation will represent the total percentage of respondents who are predicted to express that attitude.

With all four estimations, the predicted probability of individuals' attitudes falling in one of the five response options could then be calculated. For example, the percentage of respondents whose predicted attitude $\tilde{y}_1 = 1$ represents those who "strongly oppose" the ACA; and the percentage of respondents whose predicted attitude $\tilde{y}_2 = 1$ minus the percentage of respondents whose predicted attitude $\tilde{y}_1 = 1$ represents those who "oppose" the ACA. This is because $\tilde{y}_2$ includes all respondents who answered in either manner, but $\tilde{y}_1$ only indexes the respondents who said "strongly oppose;" hence the difference illustrates the size of the "oppose" category. And the same practice can be repeated to calculate the percentages of individuals who might express “neither favor nor oppose,” “favor,” and “strongly favor,” given any specific set of counterfactual data.

Results

The counterfactual predictions using linear regression analyses show that the increases in individuals’ informedness result in corresponding increases in individuals’ overall favorability of the ACA. The results are summarized in Table 6.3. Compared to the *Baseline* scenario where people hold their original beliefs and original level of certainty, in all three counterfactual scenarios, individuals’ predicted attitudes toward the ACA become more favorable.

The most critical change occurs when individuals possess correct beliefs regarding all provisions with full certainty (*Optimal* scenario)—the overall attitudes toward the ACA undergo a transition from negative to positive. Though only marginally positive, this signifies a fundamental shift, especially in light of the enduring divisiveness and equivocality that has characterized public opinion on the ACA (Gallup, 2020; KFF, 2023; Pew, 2017). This finding further corroborates the interaction effects of belief and belief certainty as identified in the analyses in Chapter 5, underscoring the significance of considering belief certainty in the process of attitude formation. The attitudinal changes reflected in the counterfactual simulations are illustrated in Figure 6.1.

Table 6.3 *Predicted Attitudes Toward the ACA Using Linear Regression Model*

Predicted attitude - Mean (SD)	Baseline .46 (.26)	All Correct .48 (.24)	Fully Certain .48 (.27)	Optimal .51 (.25)
t-tests (N = 1,344)	All Correct v. Baseline: 2.07 * Fully Certain v. Baseline: 1.97 * Optimal v. Baseline: 5.08 *** All Correct v. Fully Certain: .05 Optimal v. All Correct: 2.99 ** Optimal v. Fully Certain: 3.17 **			

Note. * p < .05; ** p < .01; *** p < .001

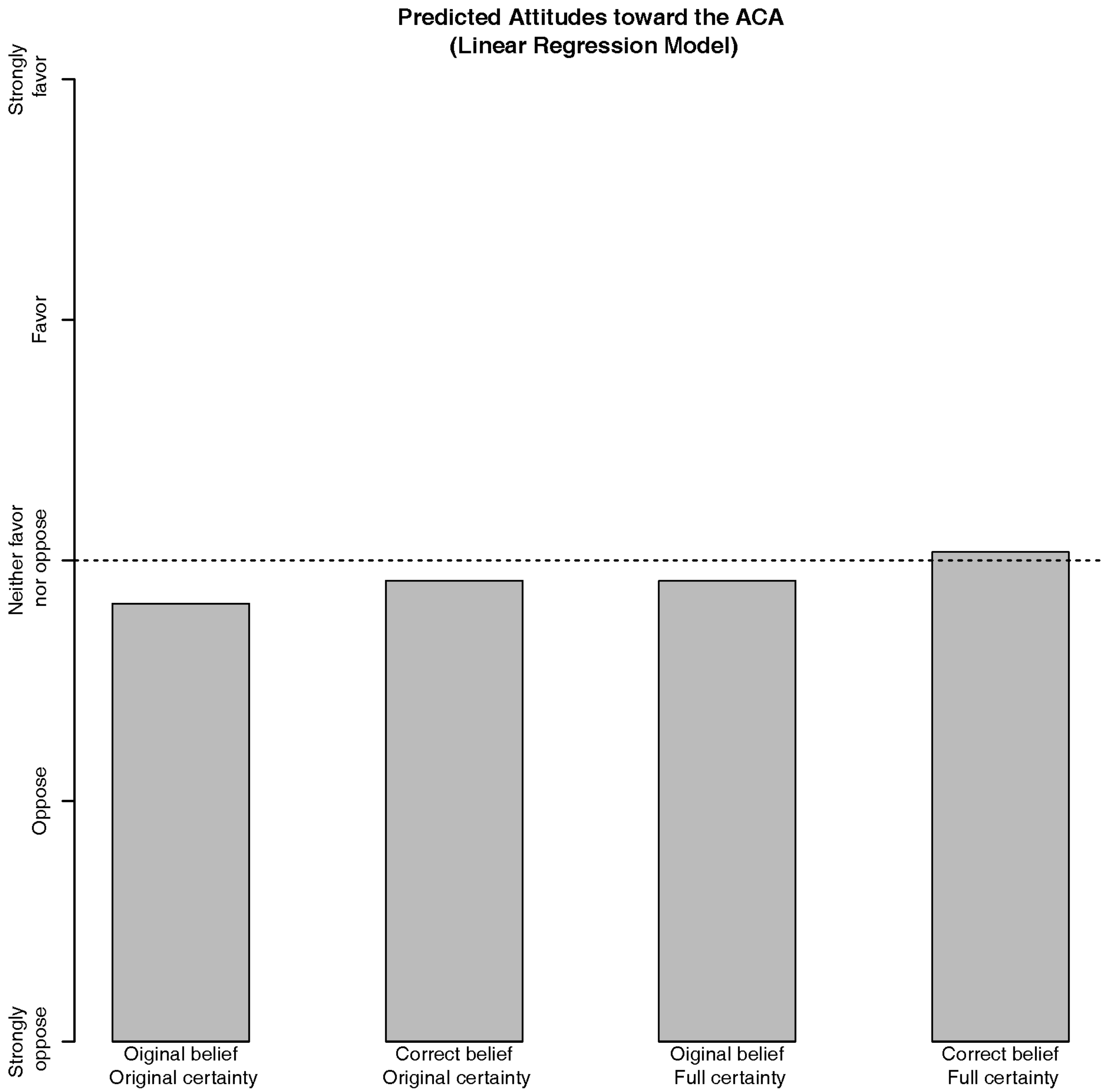

Figure 6.1 *Predicted Attitudes Across Counterfactual Scenarios (Linear Regression Model)*

The simulations using logistic regression models revealed more nuances of the effects of beliefs and belief certainties on the overall attitudes toward the ACA. As illustrated in Figure 6.2, moving from observed original beliefs to all correct beliefs with certainty level remaining unchanged (i.e., from *Baseline* to *All correct*) does seem to reduce the proportion of respondents who would express "oppose" and "strongly oppose." However, the most startling finding is the effects of belief certainty in reducing attitude ambivalence and increasing attitude extremity. In the two counterfactual scenarios where respondents were hypothesized to hold full certainty with their beliefs, the “neither favor nor oppose” group drastically shrank from 25.6% (*Baseline*) to 11.4% (*Fully certain*) and 10.9% (*Optimal*) respectively, while the proportion of individuals who are predicted to report either “strongly favor” or “strongly oppose” increased remarkably (the exact percentages are reported in Table 6.4).

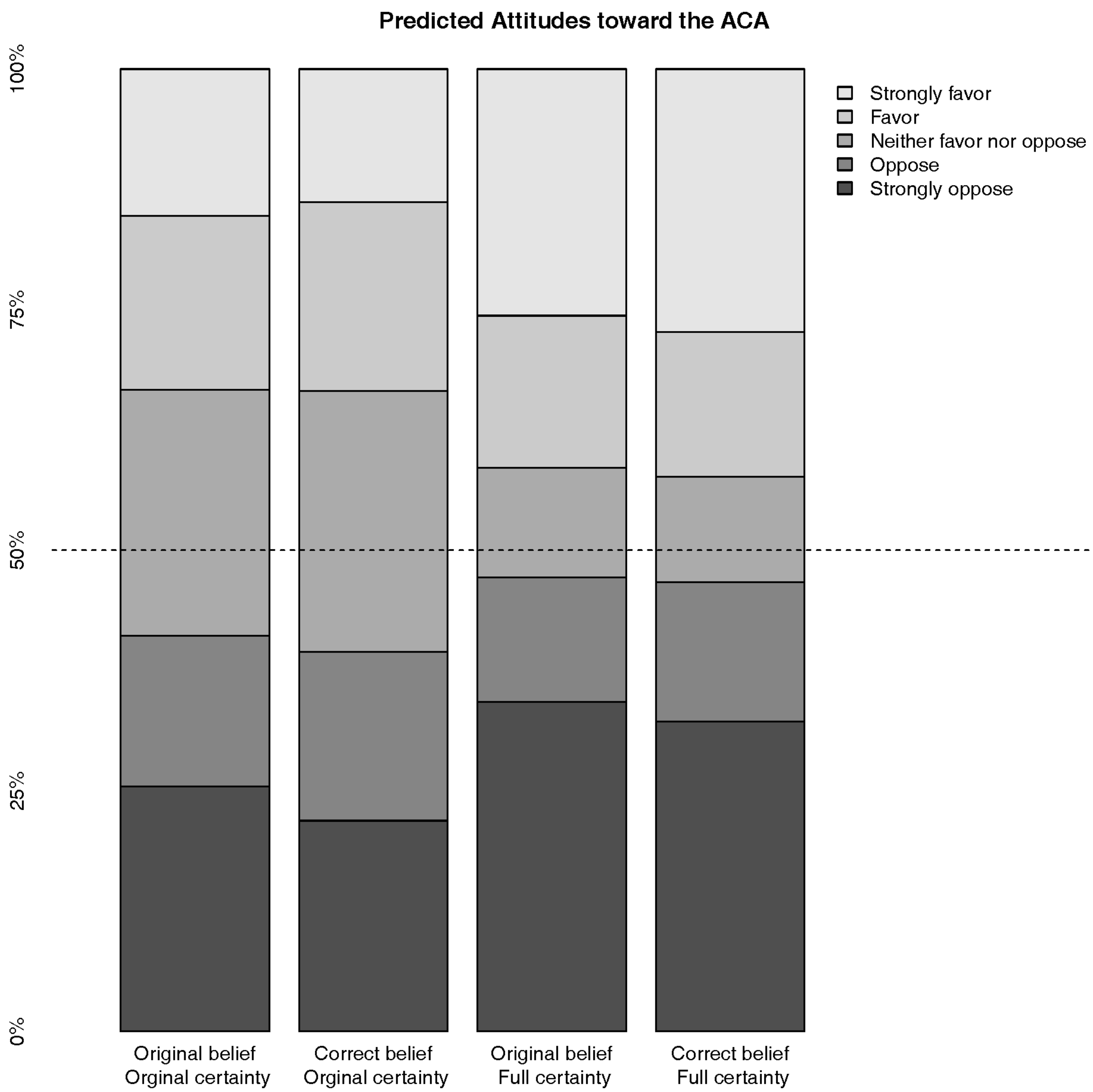

Figure 6.2 *Predicted Attitudes Across Counterfactual Scenarios (Logistic Regression Models)*

It is also worth noting that many of these percentage changes (as noted in Table 6.4) could be thought of as "statistically significant." All these percentages were calculated by averaging the predicted probability of each response option under each counterfactual scenario across 20,000 iterations. By comparing the counterfactual estimates within each iteration, we conduct an effective bootstrap of the likelihood that the probability of any given response option in one counterfactual scenario is larger than the corresponding response option in a different scenario. Hence, if we find that the proportion of individuals who "strongly oppose" the ACA in *All correct* scenario is larger than the proportion who "strongly oppose" the ACA in *Fully certain* scenario for 19,500 of the iterations, we calculate the equivalent of a p-value of .05.[8]

Table 6.4 *Predicted Attitudes Toward the ACA Using Logistic Regression Models*

Predicted attitude \ Scenario	Baseline	All Correct	Fully Certain	Optimal
Strongly oppose	25.4% [234]	21.9% [134]	34.3% [12]	32.2% [12]
Oppose	15.7%	17.6% [3]	12.9% [2]	14.5%
Neither favor nor oppose	25.6% [34]	27.1% [34]	11.4% [12]	10.9% [12]
Favor	18.1%	19.6% [34]	15.8% [2]	15.1% [2]
Strongly favor	15.3% [234]	13.8% [134]	25.6% [12]	27.3% [12]

Note. The superscripts indicate that the comparison between scenarios shows differences in at least 19,500 of the 20,000 iterations. [1]Different from Baseline; [2]Different from All Correct; [3]Different from Fully Certain; [4]Different from Optimal.

What about partisanship?

Lastly, the counterfactual simulations offer a different perspective in assessing how partisanship might influence the overall attitudes toward the ACA. As discussed in Chapter 1, the partisan effects on individuals' attitudes toward the ACA could have three different sources. First, it might be attributable to partisan differences in beliefs about the law. That is, individuals of different partisan groups simply know different things about the ACA, which has been confirmed by analyses in Chapter 4. Second, individuals with differing partisan identities might

[8] This is calculated as 2*(1-(19,500/20,000)) for a two-tailed test.

have evaluated aspects of the law differently because of their pre-existing values and ideologies. Analyses in Chapter 4 also revealed how the same provision could receive entirely different evaluations from respondents of different partisan groups. Third, the differences could stem from pure partisan considerations and might be expressive in nature—people may have evaluated the law based on which party was supporting it while ignoring the content of the law in their judgments.

One way to think about the influence of partisanship is to assess whether different individuals of different partisan groups would still express diverging attitudes toward the ACA even if members of these groups all had the same state of information or even the same evaluations of the components of the law. By simulating a public that was optimally informed about the provisions of the ACA, the role that differences in information state (beliefs and belief certainties) might have had in accounting for the partisan attitudinal gap could be estimated. And to understand the extent to which differences in the evaluations of different components of the law might be a primary driver behind partisan differences in attitudes, an additional counterfactual scenario (*Optimal + Mean*) was created. In this hypothetical public, in addition to having correct beliefs about what provisions are and are not in the ACA with full certainty, every individual also has equivalent evaluations of each of the provisions. For the purposes of this approach, respondents' evaluations of each individual provision were set at the mean value for the provision evaluation measure across the entire sample. In practice, it means that, for each provision i, $\tilde{x}_{i,1}$ (belief) reflects correct belief, $\tilde{x}_{i,2}$ (belief certainty) reflects full certainty, $\tilde{x}_{i,3}$ (provision evaluation) is the average evaluation of provision i across all respondents, and all interaction terms ($\tilde{x}_{i,4}$, $\tilde{x}_{i,5}$, $\tilde{x}_{i,6}$, and $\tilde{x}_{i,7}$) reflected correct belief, full certainty, and average evaluation as well.

Simulations of *Optimal* and *Optimal + Mean* scenarios using the linear regression model are performed for three partisan groups to assess the partisan attitudinal gap. The results are summarized in Table 6.5, which revealed both a steady increase in overall favorability of the law with increases in belief accuracy and belief certainty, and persistent attitudinal gaps across partisan groups regardless of the improvement in information states.

Table 6.5 *Predicted Attitudes Toward the ACA by Partisan Groups*

		Baseline	Optimal	Optimal + Mean
	All	.46 (.26)	.51 (.25)	.51 (.11)
Predicted attitude	Republicans	.21 (.19)	.28 (.18)	.38 (.03)
Mean (SD)	Independents	.44 (.20)	.50 (.20)	.50 (.05)
	Democrats	.68 (.16)	.71 (.15)	.63 (.04)

As illustrated in Figure 6.3, there are persistent partisan gaps across all scenarios, again suggesting that apart from being influenced by information, the public opinion on the ACA remains highly divided by partisanship. When individuals possess correct beliefs on all the provisions asked about the ACA with full certainty (*Optimal* scenario), the overall attitudes toward the law of respondents of all three partisan groups seemed to turn more favorable, suggesting that the mechanism that increases in belief accuracy and belief certainty will improve the overall favorability of the law remains effective for individuals with distinct partisan identities. However, it is also apparent that even with the optimal states of information (all correct beliefs with full certainty), the attitudinal gap across partisan groups remains non-negligible.

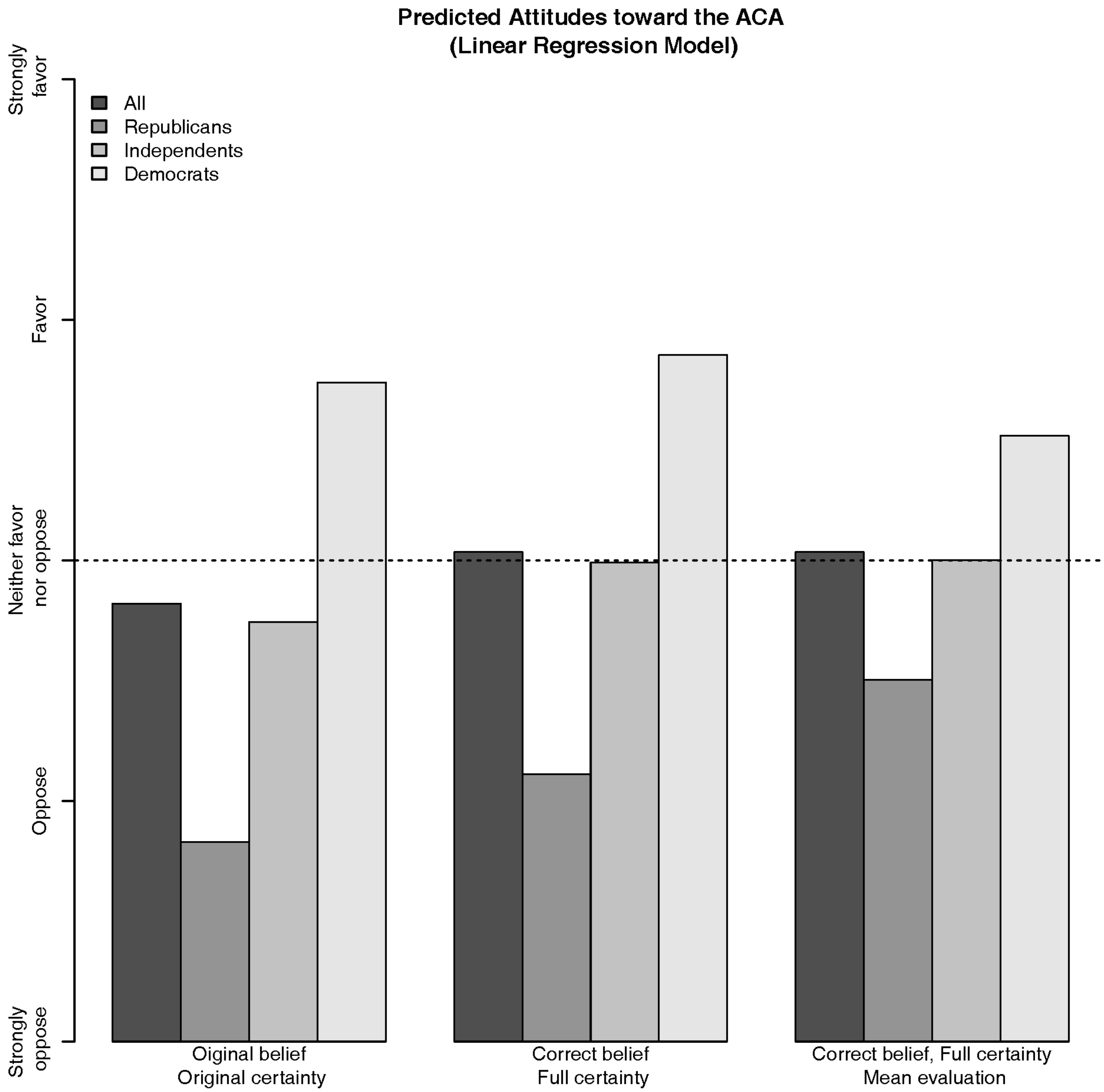

Figure 6.3 *Predicted Attitudes Across Counterfactual Scenarios by Partisan Groups*

To further understand these gaps, the partisan attitudinal differences attributable to differences in beliefs were estimated. Table 6.6 summarized the analyses. Attitudinal difference attributable to variations in information state is quantified by subtracting the average overall attitude toward the ACA of respondents of one partisan group from the average overall attitude of respondents of another partisan group, when they all have optimal states of information (*Optimal*). These differences were then divided by the average attitudinal differences between the same two groups predicted by the observed data (*Baseline*) to quantify how much of the attitudinal gap could be attributed to differences in beliefs and belief certainties. As shown in the 4^{th} column of Table 6.6, the proportions ranged from 4.3% to 12.5%, meaning that the differences are 4.3% to 12.5% smaller among an optimally informed public, depending on which partisan groups are in the comparison. Informedness would likely mitigate partisan differences, but only slightly.

A similar strategy is extended to assess the extent to which differences in the evaluations of different components of the ACA might be the primary driver behind partisan differences in overall attitudes toward the law. Attitudinal difference attributable to differences in provision evaluations is quantified by subtracting the average overall attitude toward the ACA of respondents of one partisan group from the average overall attitude of respondents of another partisan group, when they all have the optimal states of information and average evaluations of all individual provision (*Optimal* + *Mean*). These differences were then divided by the average attitudinal differences between the same two groups in the counterfactual scenario where information state is optimized while provision evaluations remained the same as observed data (*Optimal*), to quantify how much of the attitudinal gap could be attributed to differences in provision evaluations. This approach did far more to mitigate partisan differences than the counterfactual scenario where everyone had accurate beliefs about what was in the law with full certainty. Depending on the partisan groups in the comparison, these differences in the evaluations of the provisions of the law accounted for somewhere between 38.1% and 51.2% of the partisan gap in overall attitudes (Column 5, Table 6.6).

Lastly, across all comparisons, partisan differences in overall attitudes toward the law cannot be fully accounted for with either beliefs about the law and corresponding belief certainties, or evaluations of the major components of the law. These residual partisan differences were typically the largest component of the overall partisan differences (Column 6, Table 6.6), which lends support to the speculation that these attitudes might be expressive in nature. Attitudes toward the ACA are not simply an amalgam of policy assessments, but also a product of partisan identities.

Table 6.6 *Comparison of Partisan Differences Across Counterfactual Scenarios*

Mean differences in attitudes between partisan groups	Baseline	Optimal	Optimal + Mean	Difference attributable to		
				Information state	Evaluation	Partisanship
Republicans v. Independents	.23	.22	.12	4.3%	45.5%	50.2%
Republicans v. Democrats	.47	.43	.21	8.5%	51.2%	40.3%
Independents v. Democrats	.24	.21	.13	12.5%	38.1%	49.4%

Summary

This chapter conducted an investigation into the extent to which individuals' beliefs about what constitutes the ACA and their evaluations of those constituent parts might influence their overall attitudes toward the law. Leveraging a novel counterfactual simulation approach using Bayesian methods, I explored what the overall attitudes toward the ACA would look like among a fully informed public, and how to understand the partisan differences in the overall attitudes toward the law.

First, increases in belief accuracy significantly improved the law's overall favorability, and possessing correct beliefs about all provisions of the ACA with full certainty could even turn the slightly negative overall attitudes into slightly positive ones. Considering the enormous amount of dis/misinformation about the ACA and the apparently negative valence associated with those false claims (as examined in Chapter 4), correcting misperceptions about the ACA has the potential to improve public perceptions of the law, which lends realistic support to the endeavors of public education and dis/misinformation correction, as they would make a change in people's attitudes.

Second, the conclusion that improvements in information state will result in a more positive attitude toward the ACA must be taken with great caution. Chapter 5 established the important regulatory role of belief certainty in the formation of attitudes. The counterfactual simulations performed in this chapter further revealed its enormous impact on increasing attitude extremity. Though there have long been speculations on the correlation between attitude certainty and attitude strength (e.g., Krosnick et al., 1993), this project serves as the first of its kind to empirically investigate what impacts belief certainty could realistically have on political attitudes, and the results are startling. Belief certainty was found to have great effects in reducing attitude ambivalence and increasing attitude extremity. It reveals that a large portion of the so-called "neutral" group of respondents in any surveys or opinion polls might express "neither favor nor oppose" attitudes not because they truly have no inclination, but because they are not certain about the attitude object in question. If they hold beliefs about various attributes or components of the attitude object confidently, the "neither favor nor oppose" response will appear much less frequently, while a much larger proportion of the respondents will report either "strongly favor" or "strongly oppose." Moreover, this effect of belief certainty is independent of the effect of belief accuracy. In both scenarios involving full belief certainty while belief accuracy differs (*Fully Certain* and *Optimal*), an exodus from the "neither favor nor oppose" is found, so are the significant increases in "strongly oppose" and "strongly favor."

Third, the counterfactual simulation approach offers a unique perspective to scrutinize the effects of partisan identities on the overall attitudes toward the ACA. Through decomposing the partisan attitudinal differences attributable to information state (belief accuracy and belief certainty), provision evaluation, and partisan identity, it is revealed that even after accounting for the influences of differences in both information state and evaluations of individual provisions, around 40%–50% of the partisan attitudinal gap remains and could probably at best be understood as supporting the party's stand and signaling their partisan identities. Whereas a belief-based attitude model is warranted (Chapter 5) and the influences of increasing belief accuracy and belief certainty on changing attitudes are evident (this chapter), it is undeniable that the ACA remains a highly partisan issue and the public opinion divides over the law, to a large extent, might still be attributable to profound partisan divisions.

CHAPTER 7

A Concluding Remark

This dissertation project began with a simple question: Is our fervent yearning for an informed citizenry sound and justifiable, or groundless and irrational? The constant pursuit of an informed citizenry is built on the presupposition that information would empower citizens, enhance democratic participation, optimize decision-making, and contribute to a vigorous and sophisticated democracy (Brown, 1996; Delli Carpini, 2000; Dewey, 1916; Gans, 2004; Jefferson,1816; Milner, 2002; Tocqueville, 1835/2000). Despite the abundance of previous studies, to what extent this expectation reflects reality rather than wishful thinking remains a question to be answered. Through investigating American public opinion on a highly complex, contentious, and consequential public policy—the ACA, this project contributed to a better understanding of the role of information in the process of political attitude formation. Moreover, the innovative methodological tools proposed by the current study leveraging Bayesian statistical techniques have the potential to resolve a series of challenges facing existing methods. This chapter will summarize the major findings of the current project, review their theoretical and methodological contributions and implications, and discuss possible avenues for future research.

The indispensable role of belief in political attitude formation

It has long been assumed that the formation of individuals' attitudes toward a complex attitude object should reflect an integration process whereby individuals evaluate different constituent parts of the attitude object based on the information they have about these components and synthesize these evaluations to render a summary judgment (e.g., Anderson, 1962; Fishbein, 1963; Jaccard & Becker, 1985). As Fishbein and Ajzen (1975) put it, "Most people hold both positive and negative beliefs about an object, and attitude is viewed as corresponding to the total affect associated with their beliefs … a person's attitude toward some object is related to the set of his beliefs about the object but not necessarily to any specific belief" (p. 14). This rather straightforward and intuitive process, surprisingly, received relatively little empirical examination. The underlying reason for this inadequacy in empirical studies, as discussed at the beginning of this dissertation, might be that our current methods do not have the capacity to accurately estimate a large number of potentially highly correlated parameters without confronting the problems of overfitting and multicollinearity.

Leveraging Bayesian statistics with MCMC methods, this project investigated the information processing mechanism underlying complex political attitude formation and revealed how multiple informational beliefs about and evaluations of different provisions of the ACA were collectively related to Americans' overall attitudes toward the law. Through imposing a structural matrix regulating the relationships between beliefs and evaluations across different provisions of the law and the overall attitudes as an informative prior in Bayesian inference, this project successfully established a model that beliefs and evaluations associated with different attributes of an attitude object were presumed to have structurally similar relations with the overall attitude, and the variations in the effects of different beliefs and evaluations were actually determined by varying importance levels of different attributes. The informative prior component in Bayesian analysis provides the means for imposing such a constraining structure between parameters, and Bayesian estimation of parameters as random effects with posterior probability distribution through intense computations paves the way for estimating a large number of individual parameters accurately and simultaneously. This set of innovations, therefore, constituted a major contribution to addressing the methodological challenges facing existing research. More importantly, it established the theoretical validity of an informational belief-based attitude model outlining an attitude formation process whereby individuals integrate their beliefs about and evaluations of various attributes and components of a complex attitude object to form their overall attitudes toward the object.

A collateral benefit of considering various beliefs and evaluations as having structurally similar relations to the overall attitudes while the unique effect was contributed by the relative importance of different attributes is that it helps reconcile the theoretical and methodological debate on whether belief importance should be considered as a separate variable in the expectancy-value model of attitude. On the one hand, it is simply nonsensical to expect that different attributes or components of an attitude object would not bear unequal weights but have equivalent impacts on the overall attitudes, and empirical studies did reveal that compared to attributes being perceived as less important, the evaluations of attributes deemed more important had a higher correlation with the overall attitudes (van der Pligt and de Vries, 1998a, 1998b; van Harreveld et al., 2000). On the other hand, the idea of adding belief importance as an additional multiplicative variable to the model was rejected by Fishbein and Ajzen (2010) because they believe that measures of beliefs and attribute evaluations should have sufficiently captured subjective belief importance, rendering any separate assessment of the variable redundant. And past research did suggest that adding belief importance as an additional multiplicative variable to the model has little discernible effect on the prediction of attitude (Kenski & Fishbein, 2005). This finding, however, may be more reflective of empirical multicollinearity than conceptual overlap. The current study proposed the method to decompose the effects of individual beliefs and evaluations into the uniform influences of belief and evaluation across all attributes and the unique importance or weight associated with different attributes. The method thus confirms belief importance as a valid construct to be considered in the model without adding it as a redundant multiplicative variable, which is another example of how methodological innovations help address theoretical questions.

The central role of informational belief in the process of attitude formation was further corroborated by a series of counterfactual simulations of a better-informed public. Across various hypothetical scenarios using distinct estimation methods, an increased belief accuracy has been consistently found to improve the overall favorability of the ACA. These simulation works actually highlighted an interesting void in the literature on dis/misinformation and belief accuracy, because most past studies on correcting misperception have focused on whether the action of belief updating itself was successful, i.e., whether the misperception was corrected (e.g., Flynn et al., 2017; Nyhan & Reifler, 2010). In contrast, relatively few studies have looked into whether corrections altered attitudes associated with the updated beliefs. Nevertheless, because the reason for correcting misperceptions is presumably to mitigate a deleterious impact on attitude formation and decision-making, these downstream processes should be thoroughly investigated. The changed overall attitudes ensued from increased belief accuracy that this project identified lends realistic support to the effectiveness of public education and dis/misinformation correction endeavors. In response to concerns about the state of citizens' political awareness, scholars have long sought to understand what ideal policies and political behaviors might look like by imagining what a more sophisticated public would think (e.g., Bartels, 2005; Lau & Redlawsk, 1997; Luskin, 2003; Sturgis, 2003). Although a hypothetical "fully informed" public is surely nothing more than a fantasy, to consider how a counterfactual, knowledgeable public would differ in their policy attitudes or voting preferences provides a metric for understanding the collective impacts of political information.

The profound impact of belief certainty

Another major finding of this project is that it identified the pivotal role of belief certainty in the process of attitude formation, which was largely overlooked in prior research. Other than holding varying beliefs about the attitude object, the extent to which individuals are confident in the beliefs that they hold is also likely to vary. The revised belief-based attitude model proposed by this project revealed that beliefs held with certainty have exerted greater influences on the overall attitudes toward the ACA compared to those uncertain ones. For a provision that was believed to be part of the law, favoring that provision would lead to a more positive overall attitude if that belief was held with greater certainty. For a provision that was believed to be not in the ACA, a more positive evaluation of that provision would indeed decrease the overall favorability of the law if that belief was held confidently; yet a similar effect did not exist when the belief was held with no certainty. All these findings indicate the important regulatory role of belief certainty in the attitude formation process by moderating how beliefs and attribute evaluations influence overall attitudes. A belief held with minimum confidence is probably not going to have much of an effect on attitude formation and decision-making, whereas a belief held with great certainty is likely to be much more consequential.

The impact of belief certainty is not merely limited to determining which belief matters more and which matters less in the attitude formation process. The counterfactual simulations leveraging logistic regression models revealed more nuances of how changing states of information influenced the overall attitudes, and the most critical finding is that the growth in belief certainty considerably increased attitude extremity. The size of the “neutral” group diminished by more than 55% while the group of those who expressed strong preferences (either favor or oppose) expanded enormously. This was not a finding that was initially hypothesized or expected, mostly because the domain of belief certainty was rather underexplored and there were no presumptive expectations formulated before the counterfactual simulations were performed (though early attitude strength literature did suggest a correlation between attitude certainty and attitude strength, see Krosnick et al., 1993). But upon careful consideration, the inherent logic in this matter is indeed quite apparent. Given the central role of belief in the attitude formation process, one of the sources of ambivalence in one's attitude (i.e., lacking a clear preference or inclination toward either end of the evaluative spectrum and appearing "neutral") might be that she or he does not know enough about the attitude object confidently. The lack of certainty in their beliefs discounted the influence exerted by attribute evaluations because these two variables were multiplied by each other in the revised expectancy-value model of attitude. But when a belief about an attribute is held with greater certainty, the evaluation of that attribute will have more of an effect on the overall attitude, resulting in an increase in the magnitude of the outcome variable.

This finding might have more realistic implications. For one, many scholars argue that only correct beliefs held with certainty could be considered as knowledge because correct answers to knowledge quiz questions with no certainty might simply reflect random guessing (Chinn & Pasek, 2021; Li & Wagner, 2020). To become more knowledgeable, therefore, requires not only possessing correct beliefs but also having confidence in those beliefs. Whereas we might still hold onto the tenet that a more knowledgeable public is a better public, the association between belief certainty and attitude extremity reveals a possible side effect of holding beliefs confidently, which is that the public attitudes are likely to be more polarized, even if all the beliefs people hold were accurate. This polarization might be further amplified because beliefs are not distributed evenly among the public, and a considerable number of beliefs are actually inaccurate.

The persistent partisan gap

The polarization predicted by the counterfactual simulations is just another addition to the discrepancies identified by the current project. Descriptive analyses first revealed constant information disparity. Even though there was no clear pattern that any particular partisan group is systematically more knowledgeable about the ACA than others, in terms of correctly identifying provisions in the law, Republicans were apparently more misinformed about the law because they were consistently more likely to accept the false claims regarding the law as factual. This difference in the state of information, i.e., individuals of different partisan groups possess different beliefs about what the ACA consists of, is the first element that might account for the observed partisan gap in attitudes. Ideally, this part of the discrepancy might be alleviated if individuals of different partisan groups were generally better-informed.

The partisan gap in the evaluations of individual provisions, in contrast, can hardly be mitigated through pure information intervention efforts. The provision that companies with 50 or more employees should be required to provide health insurance was enthusiastically supported by Democrats but not welcomed by Republicans. The idea that undocumented immigrants might receive free medical treatments, which is an utterly false claim, was loathed by Republicans while only being found marginally unacceptable by Democrats. Although this dissertation did not extend to investigate the underlying causes of partisan gaps in the evaluations of different provisions, it seems apparent that these evaluative differences are rooted in the fundamental discrepancy in values and ideologies that different partisan groups embrace. Whereas the efforts of correcting dis/misinformation might succeed in educating Republicans to believe that the ACA would not require health care providers to treat undocumented immigrants for free (to what extent this can actually succeed is another question), it is probably beyond the sheer capacity of information to persuade individuals of different partisan groups to have less diverging views on the stipulation that employers must provide health insurance.

Admittedly, the partisan differences in evaluations of individual provisions are probably less of a concern because we tend to see these differences as genuine and sincere—they simply reflect different views of the world. An informed citizenry does not need to be, and in fact should never be, a homogeneous public. Diversity and inclusivity are the defining features of a healthy, robust democracy (Barber, 1998; Gutmann & Thompson, 1996). Respect for different political views is particularly essential to foster an environment where individuals can openly express their opinions and engage in constructive debates. By respecting and acknowledging the legitimacy of opposing political stances, a democratic system could promote social cohesion and a sense of shared purpose among its citizens (Mills, 1859; Sunstein, 2005). Efforts could of course be made to reconcile these evaluative differences in order to achieve a greater societal consensus, but in general, these evaluative differences are not inherently problematic as long as they are not based on inaccurate information and fallacious accusations fabricated with political motivations.

The more alarming reality of the persistent partisan divide comes from the part of the attitudinal discrepancies that were not attributable to either disparities in information states or differences in provision evaluations. The counterfactual simulations revealed that around 40%–50% of the attitudinal gaps remained unaccounted for. It is possible that this part of the attitudinal discrepancies still stems from differences in states of information about and evaluations of provisions, but these provisions were not covered by the data collected for this project. Yet considering the comprehensiveness of the survey, a more likely explanation would probably be that these attitudinal gaps reflected some more fundamental partisan divides. Whether they are expressive in nature as a product of partisan identity signaling, as suggested by many scholars working on political polarization (e.g., Bullock et al., 2015; Huddy et al., 2015; Malka & Adelman, 2022; Prior et al., 2015; Schaffner et al., 2018; Shino et al., 2023), or reflect some other profound partisan considerations, requires further scrutiny. However, it stands to reason that this part of the partisan discrepancies, just as differences in provision evaluations, probably cannot be mitigated by improvements in people's states of information. The public opinion divide over the ACA reflects the continuing relevance of partisan identity. Whereas the belief-based attitude model appears to operate similarly across partisan groups such that holding beliefs with certainty is essential in individuals' political attitude formation process regardless of their partisan identities, we have to recognize that information is not omnipotent and there is a boundary beyond which the influence of increasing belief accuracy becomes limited.

Future directions

No research is beyond criticism, and this dissertation is no exception. But given the methodological innovations and implications of the findings of the current project, there are several promising directions that this line of research could take in the future to address the inadequacies.

First, what are the sources of information disparities across partisan groups? A critical feature of public opinion on the ACA is the quantity and intensity of dis/misinformation in political debates and public discourse. The pervasiveness of misperceptions on this issue came into existence long before the political information environment that was allegedly infused with "fake news" as we know of today. When the former governor of Alaska and Republican vice-presidential nominee Sarah Palin coined the term "death panel," which was dubbed by some media as "Lie of the Year" (Holan, 2009), even Twitter was not launched for very long, and terms like "post-truth politics" or the prospect that Donald Trump would be elected U.S. president one day were surely nowhere to be seen. Nevertheless, this myth just successfully stood the test of time and even elicited questions like "Why the 'death panel' myth wouldn't die?" (Gonyea, 2017; Nyhan, 2010). Because of the central role of belief in the political attitude formation process as identified by the current project, it is important to investigate the determinants of people's states of information, in particular, the effects of traditional news media and social media platforms on shaping individuals' cognitive beliefs about the law, and how varying media usage contribute to the partisan disparities in individuals' beliefs about what the law will or will not do.

Second, the cross-sectional nature of the data limits this project's ability to make causal claims. Although the results fit neatly with the notion that people use beliefs to derive overall attitudes, there is a possibility that these beliefs reflect post hoc rationalizations guided by attitudes. This seems unlikely though, given the complexity of the model with many moving parts, and the finding that the observed data fit well with the proposed optimization process based on a weighted linear combination of three-way multiplicative terms for 18 distinct provisions, but the possibility cannot be completely ruled out. Longitudinal data needs to be collected and analyzed to better establish causality. Furthermore, although counterfactual simulations offered a new perspective to assess the potential impact of belief updating and dis/misinformation correction, the traditional information intervention approach still has its unique advantage in assessing whether these effects hold with actual individuals rather than hypothetical ones. The dataset used by the current research has an information intervention component. At the end of the survey, respondents were told which of the 18 provisions were in the law and which were not. Following this intervention, respondents were asked to indicate their overall attitude toward the law again. These responses could be compared to their earlier answers to assess the effects of belief updating and evaluate the accuracy of predicted attitudes and the overall validity of the counterfactual simulation models.

Third, there is a debate between “summation” and “averaging” in attitude literature concerning how individuals process information when forming attitudes (Anderson, 1971). The summation model, which is the approach that the current project adopted, suggests that attitudes are formed by summing up weighted evaluations of relevant information (Fishbein, 1963; Fishbein & Ajzen, 1975). The averaging model, in contrast, proposes calculating the mean of those evaluations (Anderson, 1965; Weaver et al., 2007). The data used by the current project does not allow for estimating attitude changes followed by every encounter with new information. However, the Bayesian model that the current project proposed, has the potential to assess whether the attitudinal changes ensued from receiving and accepting a new piece of information, if any, are more reflective of a summation procedure or more proximate to an averaging mechanism. This would further allow us to examine to what extent people really act as quasi-Bayesian updaters.

To what extent does information influence citizens’ political attitudes? This dissertation, perhaps surprisingly, suggests that there is no simple correct answer to this question. However, the theoretical model and methodological innovations proposed by this dissertation did exhibit the potential in addressing a series of challenges facing existing research and contributed to a better understanding of the crucial role of information in political attitude formation. In a world where terms are easily coined, facts flimsily represented, and beliefs conveniently molded through an ever-unsettling media ecology, it would be naive to assume that anything alone could serve as the magic potion that could alleviate our disillusionment with the broken dream of either a truly informed citizenry or a bona fide deliberative democracy. In a sad way, Walter Lippmann's (1925) phantom public metaphor stands, laying bare that human beings are only entitled to heavily veiled glimpse of reality no matter how confidently informed we assume ourselves to be. However, with a slightly more buoyant attitude, such a situation might well lead us to a vast virgin land of new thinking patterns, where novel, probably even luscious fruits can grow out of the epistemological epiphany we have just had and the crude, charming levelheadedness it has promised. Lamentation goes nowhere, and let's just keep our sociological imagination alive.

APPENDICES

APPENDIX I

RStan Coding for Full Bayesian Linear Regression Model

```
data {
 int<lower = 0> N; //number of respondents
 int<lower = 0> J; //number of coefficients per provision
 int<lower = 0> I; //number of provisions
 int<lower = 0> D; //number of demographic covariates
 matrix[N, I*J] x; //provision predictors matrix
 matrix[N, D] d; //covariate predictors matrix
 vector[N] p; //partisanship
 vector[N] y; //overall attitude
}
parameters {
 real alpha; //intercept
 real gamma; // partisanship coefficients
 vector[D] delta; //demographic covariates coefficients
 vector[J] tau; //provision predictors coefficients
 vector<lower = 0, upper = 1>[I] omega; //estimated provision importance (informative prior)
 real epsilon; // error term
}
transformed parameters {
 vector[I*J] lambda; //structural constraints (informative prior)
  for (j in 1:J){
   for (i in 1:I){
    lambda[I*(j-1)+i] = omega[i] * tau[j]
  }
 }
}
model {
y ~ normal(alpha + lambda * x + gamma * p + delta * d, epsilon); //likelihood function
}
```

APPENDIX II

Diagnostics for Provision Importance (ω_i) and Individual Belief-related Variable ($\lambda_{i,j}$)

Table II.1 *Diagnostic Statistics for Bayesian Inference (Provision Importance)*

	ESS	R-hat
Death panel (ω_1)	19406	1.000
Drug companies fee (ω_2)	20288	1.000
Individual mandate (ω_3)	17856	1.000
Make insurance for sale (ω_4)	20329	1.000
Subsidize low income (ω_5)	19720	1.000
ID Card (ω_6)	20137	1.000
Undocumented immigrants free (ω_7)	19385	1.000
Insurance companies fee (ω_8)	19439	1.000
No dropped coverage (ω_9)	19817	1.000
No capped coverage (ω_{10})	19726	1.000
Cover under 26 (ω_{11})	18719	1.000
No preexisting condition denial (ω_{12})	19653	1.000
Employer must provide (ω_{13})	19554	1.000
Subsidize seniors (ω_{14})	18821	1.000
Smoker fee (ω_{15})	19241	1.000
Soda tax (ω_{16})	20076	1.000
Small business tax credits (ω_{17})	19740	1.000
Disclose illness to employers (ω_{18})	19342	1.000

Table II.2 *Diagnostic Statistics for Bayesian Inference (Individual Belief-related Variable)*

Parameter	ESS	R-hat	Parameter	ESS	R-hat	Parameter	ESS	R-hat
$\lambda_{1,1}$	19468	1.000	$\lambda_{1,2}$	20640	1.000	$\lambda_{1,3}$	19171	1.000
$\lambda_{1,4}$	20064	1.000	$\lambda_{1,5}$	19939	1.000	$\lambda_{1,6}$	20060	1.000
$\lambda_{1,7}$	19175	1.000	$\lambda_{2,1}$	19395	1.000	$\lambda_{2,2}$	19003	1.000
$\lambda_{2,3}$	19795	1.000	$\lambda_{2,4}$	19228	1.000	$\lambda_{2,5}$	19392	1.000
$\lambda_{2,6}$	19276	1.000	$\lambda_{2,7}$	19176	1.000	$\lambda_{3,1}$	19380	1.000
$\lambda_{3,2}$	20122	1.000	$\lambda_{3,3}$	19644	1.000	$\lambda_{3,4}$	19701	1.000
$\lambda_{3,5}$	19147	1.000	$\lambda_{3,6}$	19092	1.000	$\lambda_{3,7}$	17953	1.000
$\lambda_{4,1}$	19778	1.000	$\lambda_{4,2}$	18643	1.000	$\lambda_{4,3}$	20083	1.000
$\lambda_{4,4}$	18489	1.000	$\lambda_{4,5}$	18976	1.000	$\lambda_{4,6}$	19903	1.000
$\lambda_{4,7}$	17949	1.000	$\lambda_{5,1}$	18283	1.000	$\lambda_{5,2}$	20330	1.000
$\lambda_{5,3}$	18059	1.000	$\lambda_{5,4}$	18941	1.000	$\lambda_{5,5}$	19597	1.000
$\lambda_{5,6}$	19791	1.000	$\lambda_{5,7}$	18765	1.000	$\lambda_{6,1}$	19543	1.000
$\lambda_{6,2}$	19887	1.000	$\lambda_{6,3}$	20286	1.000	$\lambda_{6,4}$	20375	1.000
$\lambda_{6,5}$	20297	1.000	$\lambda_{6,6}$	20455	1.000	$\lambda_{6,7}$	20150	1.000
$\lambda_{7,1}$	20275	1.000	$\lambda_{7,2}$	20601	1.000	$\lambda_{7,3}$	19951	1.000
$\lambda_{7,4}$	20145	1.000	$\lambda_{7,5}$	20348	1.000	$\lambda_{7,6}$	19812	1.000
$\lambda_{7,7}$	19702	1.000	$\lambda_{8,1}$	20242	1.000	$\lambda_{8,2}$	19274	1.000
$\lambda_{8,3}$	20059	1.000	$\lambda_{8,4}$	19943	1.000	$\lambda_{8,5}$	19533	1.000
$\lambda_{8,6}$	18878	1.000	$\lambda_{8,7}$	19380	1.000	$\lambda_{9,1}$	17917	1.000
$\lambda_{9,2}$	19631	1.000	$\lambda_{9,3}$	18577	1.000	$\lambda_{9,4}$	19957	1.000
$\lambda_{9,5}$	18158	1.000	$\lambda_{9,6}$	18336	1.000	$\lambda_{9,7}$	19866	1.000
$\lambda_{10,1}$	18052	1.000	$\lambda_{10,2}$	18211	1.000	$\lambda_{10,3}$	20260	1.000
$\lambda_{10,4}$	18129	1.000	$\lambda_{10,5}$	18477	1.000	$\lambda_{10,6}$	19390	1.000
$\lambda_{10,7}$	20004	1.000	$\lambda_{11,1}$	18748	1.000	$\lambda_{11,2}$	19562	1.000
$\lambda_{11,3}$	20293	1.000	$\lambda_{11,4}$	20180	1.000	$\lambda_{11,5}$	19955	1.000
$\lambda_{11,6}$	20148	1.000	$\lambda_{11,7}$	19897	1.000	$\lambda_{12,1}$	20156	1.000
$\lambda_{12,2}$	19934	1.000	$\lambda_{12,3}$	19495	1.000	$\lambda_{12,4}$	20622	1.000
$\lambda_{12,5}$	19964	1.000	$\lambda_{12,6}$	19537	1.000	$\lambda_{12,7}$	19794	1.000
$\lambda_{13,1}$	20055	1.000	$\lambda_{13,2}$	20057	1.000	$\lambda_{13,3}$	19357	1.000
$\lambda_{13,4}$	20147	1.000	$\lambda_{13,5}$	20019	1.000	$\lambda_{13,6}$	19279	1.000
$\lambda_{13,7}$	19900	1.000	$\lambda_{14,1}$	20217	1.000	$\lambda_{14,2}$	19734	1.000
$\lambda_{14,3}$	20263	1.000	$\lambda_{14,4}$	19955	1.000	$\lambda_{14,5}$	20121	1.000
$\lambda_{14,6}$	19973	1.000	$\lambda_{14,7}$	19564	1.000	$\lambda_{15,1}$	19758	1.000
$\lambda_{15,2}$	19463	1.000	$\lambda_{15,3}$	20236	1.000	$\lambda_{15,4}$	19677	1.000
$\lambda_{15,5}$	19530	1.000	$\lambda_{15,6}$	20081	1.000	$\lambda_{15,7}$	19352	1.000
$\lambda_{16,1}$	20057	1.000	$\lambda_{16,2}$	19811	1.000	$\lambda_{16,3}$	19583	1.000
$\lambda_{16,4}$	19866	1.000	$\lambda_{16,5}$	20303	1.000	$\lambda_{16,6}$	19972	1.000
$\lambda_{16,7}$	20251	1.000	$\lambda_{17,1}$	20034	1.000	$\lambda_{17,2}$	20094	1.000
$\lambda_{17,3}$	19744	1.000	$\lambda_{17,4}$	20086	1.000	$\lambda_{17,5}$	19733	1.000

$\lambda_{17,6}$	19726	1.000	$\lambda_{17,7}$	19976	1.000	$\lambda_{18,1}$	19655	1.000
$\lambda_{18,2}$	19329	1.000	$\lambda_{18,3}$	19826	1.000	$\lambda_{18,4}$	19068	1.000
$\lambda_{18,5}$	20121	1.000	$\lambda_{18,6}$	19602	1.000	$\lambda_{18,7}$	19706	1.000

Note. Provision i – Death panel ($i = 1$); Drug companies fee ($i = 2$); Individual mandate ($i = 3$); Make insurance for sale ($i = 4$); Subsidize low income ($i = 5$); ID Card ($i = 6$); Undocumented immigrants free ($i = 7$); Insurance companies fee ($i = 8$); No dropped coverage ($i = 9$); No capped coverage ($i = 10$); Cover under 26 ($i = 11$); No preexisting condition denial ($i = 12$); Employer must provide ($i = 13$); Subsidize seniors ($i = 14$); Smoker fee ($i = 15$); Soda tax ($i = 16$); Small business tax credits ($i = 17$); Disclose illness to employers ($i = 18$). Belief-related variable j – belief ($j = 1$); belief certainty ($j = 2$); provision evaluation ($j = 3$); belief × belief certainty ($j = 4$); belief × provision evaluation ($j = 5$); belief certainty × provision evaluation ($j = 6$); belief × belief certainty × provision evaluation ($j = 7$).

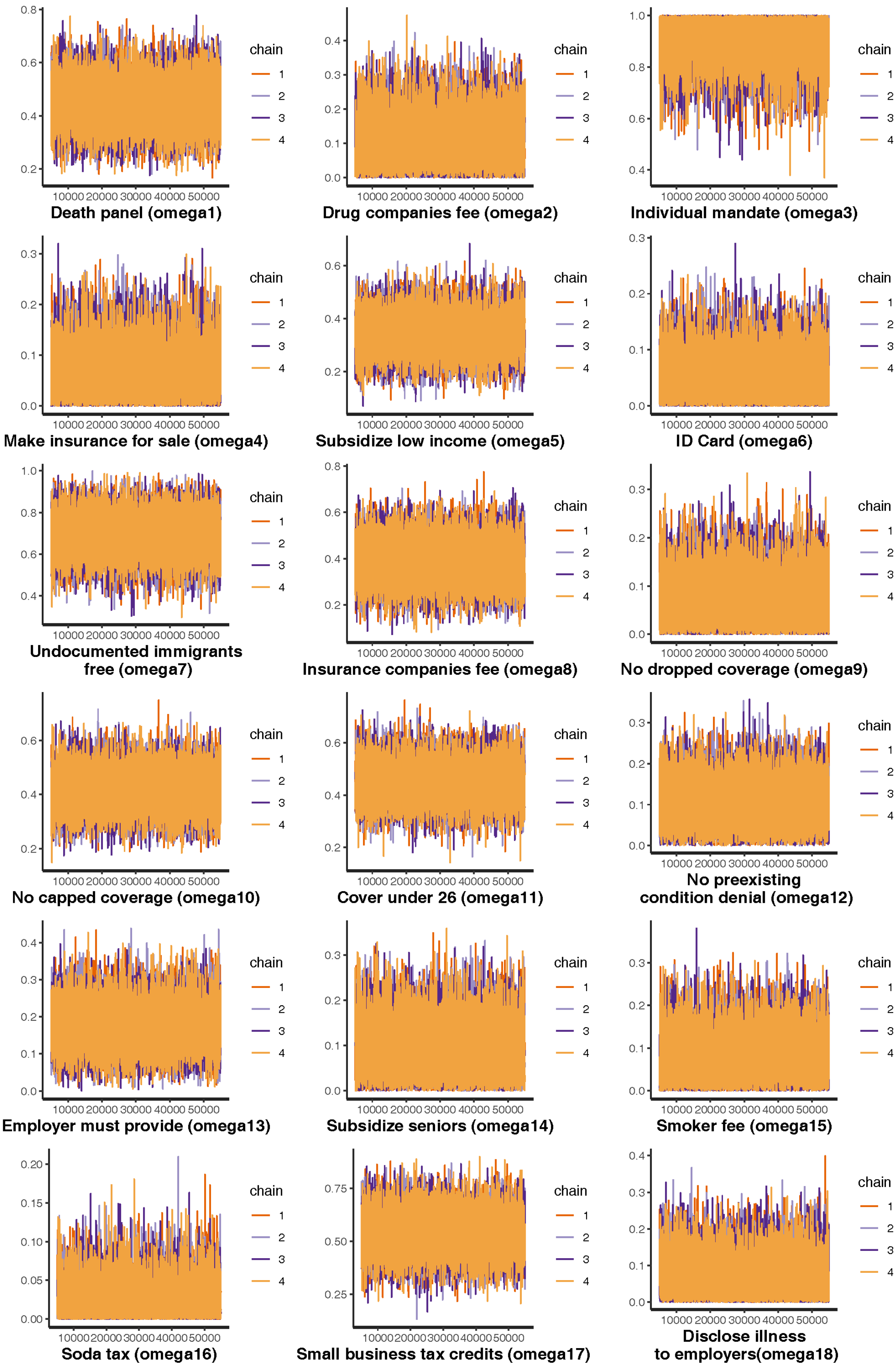

Figure II.1 *Trace Plots for Provision Importance*

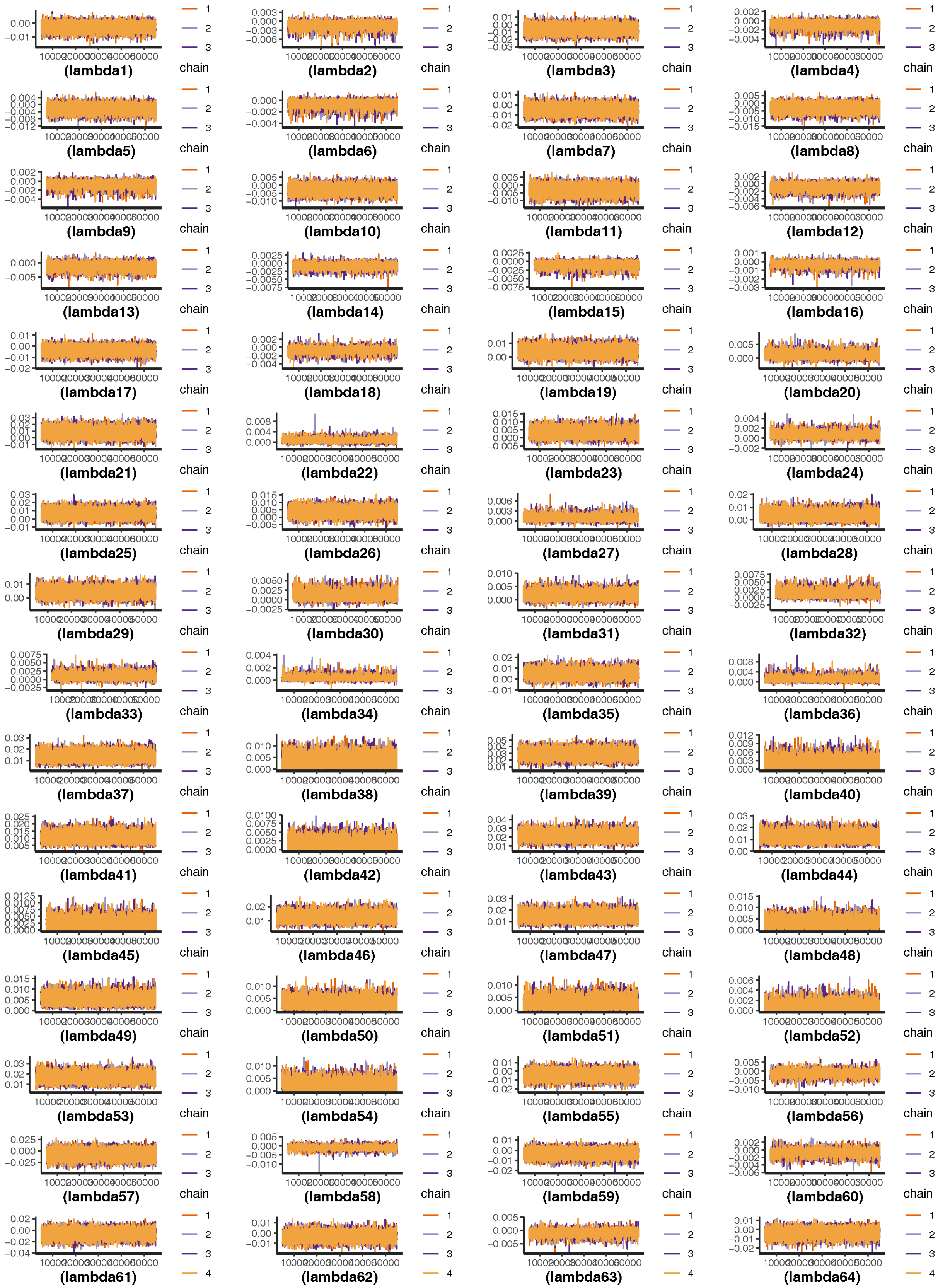

Figure II.2 *Trace Plots for Individual Belief-related Variable (1/2)*

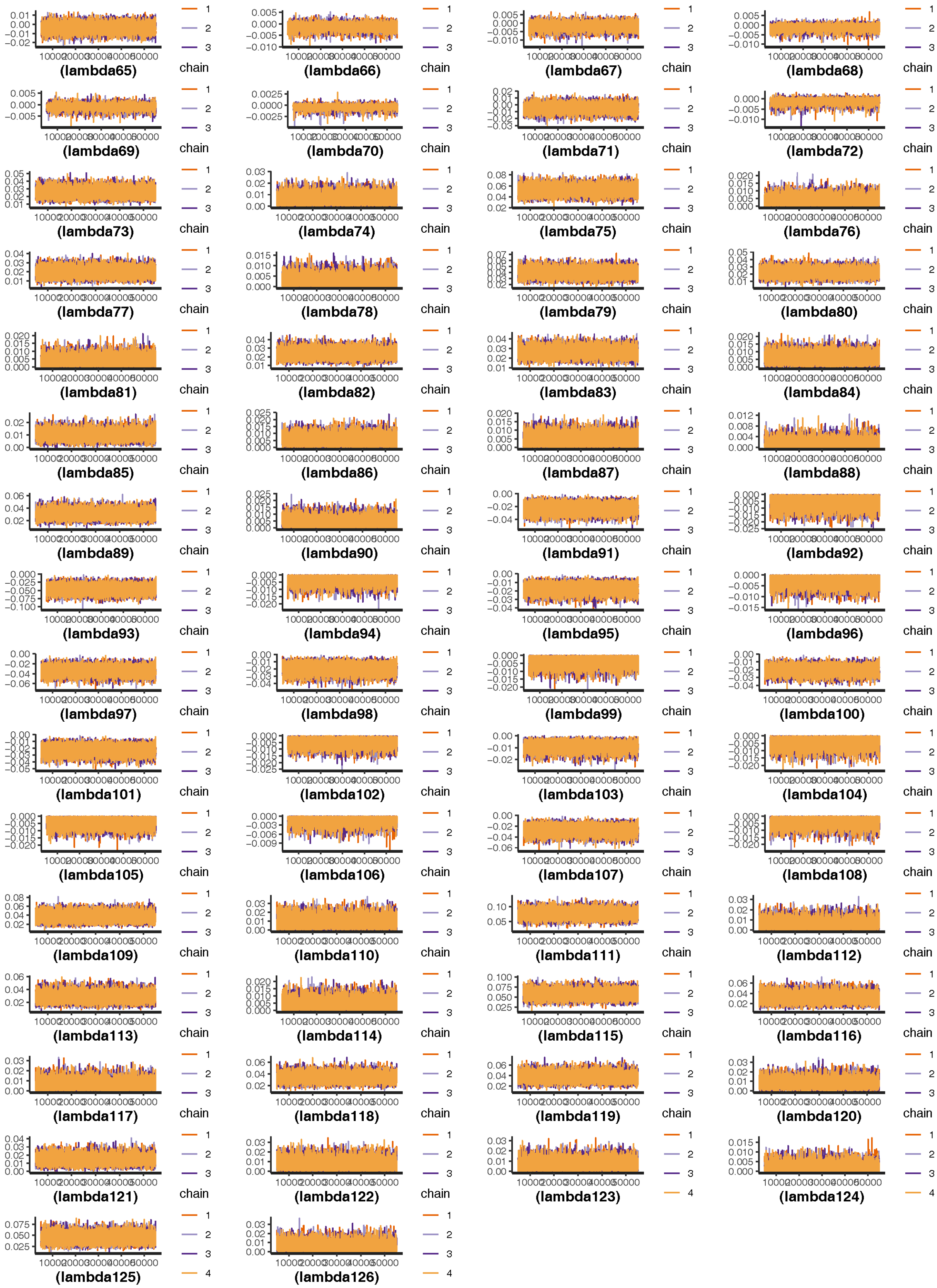

Figure II.3 *Trace Plots for Individual Belief-related Variable (2/2)*

APPENDIX III

Full Parameter Estimates of Provision Importance

Table III.1 *Bayesian Estimation of Provision Importance*

	Mean	95% HDI
Death panel (ω_1)	.446	[.287, .613]
Drug companies fee (ω_2)	.108	[.006, .264]
Individual mandate (ω_3)	.917	[.714, .998]
Make insurance for sale (ω_4)	.064	[.003, .179]
Subsidize low income (ω_5)	.342	[.203, .486]
ID Card (ω_6)	.050	[.002, .145]
Undocumented immigrants free (ω_7)	.692	[.499, .873]
Insurance companies fee (ω_8)	.384	[.215, .566]
No dropped coverage (ω_9)	.067	[.003, .185]
No capped coverage (ω_{10})	.416	[.276, .558]
Cover under 26 (ω_{11})	.452	[.310, .597]
No preexisting condition denial (ω_{12})	.104	[.012, .220]
Employer must provide (ω_{13})	.174	[.064, .294]
Subsidize seniors (ω_{14})	.094	[.007, .221]
Smoker fee (ω_{15})	.080	[.004, .204]
Soda tax (ω_{16})	.023	[.001, .080]
Small business tax credits (ω_{17})	.539	[.355, .732]
Disclose illness to employers (ω_{18})	.068	[.002, .198]

APPENDIX IV

RStan Coding for Partisan Bayesian Linear Regression Model

```
data {
 int<lower = 0> N; //number of respondents
 int<lower = 0> J; //number of coefficients per provision
 int<lower = 0> I; //number of provisions
 int<lower = 0> D; //number of demographic covariates
 matrix[N, I*J] x; //provision predictors matrix
 matrix[N, D] d; //covariate predictors matrix
 vector[N] y; //overall attitude
}
parameters {
 real alpha; //intercept
 vector[D] delta; //demographic covariates coefficients
 vector[J] tau; //provision predictors coefficients
 vector<lower = 0, upper = 1>[I] omega; //estimated provision importance (informative prior)
 real epsilon; // error term
}
transformed parameters {
 vector[I*J] lambda; //structural constraints (informative prior)
  for (j in 1:J){
   for (i in 1:I){
    lambda[I*(j-1)+i] = omega[i] * tau[j]
  }
 }
}
model {
y ~ normal(alpha + lambda * x + delta * d, epsilon); //likelihood function
}
```

APPENDIX V

Model Diagnostics for Bayesian Analyses by Partisan Groups

Table V.1 *Model Diagnostic Statistics for Bayesian Inference (Republicans)*

	ESS	R-hat
Intercept (α)	19202	1.000
Age (δ_1)	20120	1.000
Gender (δ_2)	19591	1.000
White (δ_3)	19753	1.000
Black (δ_4)	19803	1.000
Hispanic (δ_5)	19722	1.000
Education (δ_6)	20112	1.000
Income (δ_7)	19668	1.000
Belief (τ_1)	18628	1.000
Belief certainty (τ_2)	19408	1.000
Attribute evaluation (τ_3)	19687	1.000
Belief × Belief certainty (τ_4)	19165	1.000
Belief × Attribute evaluation (τ_5)	19936	1.000
Belief certainty × Attribute evaluation (τ_6)	19535	1.000
Belief × Belief certainty × Attribute evaluation (τ_7)	19572	1.000

Table V.2 *Model Diagnostic Statistics for Bayesian Inference (Independents)*

	ESS	R-hat
Intercept (α)	19509	1.000
Age (δ_1)	19930	1.000
Gender (δ_2)	19547	1.000
White (δ_3)	20166	1.000
Black (δ_4)	20328	1.000
Hispanic (δ_5)	19632	1.000
Education (δ_6)	19655	1.000
Income (δ_7)	20249	1.000
Belief (τ_1)	19657	1.000
Belief certainty (τ_2)	18198	1.000
Attribute evaluation (τ_3)	19567	1.000
Belief × Belief certainty (τ_4)	18418	1.000
Belief × Attribute evaluation (τ_5)	18845	1.000
Belief certainty × Attribute evaluation (τ_6)	19062	1.000
Belief × Belief certainty × Attribute evaluation (τ_7)	20354	1.000

Table V.3 *Model Diagnostic Statistics for Bayesian Inference (Democrats)*

	ESS	R-hat
Intercept (α)	19655	1.000
Age (δ_1)	20223	1.000
Gender (δ_2)	19638	1.000
White (δ_3)	19509	1.000
Black (δ_4)	20049	1.000
Hispanic (δ_5)	19503	1.000
Education (δ_6)	19797	1.000
Income (δ_7)	19429	1.000
Partisanship (γ)	19844	1.000
Belief (τ_1)	19883	1.000
Belief certainty (τ_2)	20205	1.000
Attribute evaluation (τ_3)	19807	1.000
Belief × Belief certainty (τ_4)	19547	1.000
Belief × Attribute evaluation (τ_5)	20143	1.000
Belief certainty × Attribute evaluation (τ_6)	19861	1.000
Belief × Belief certainty × Attribute evaluation (τ_7)	19655	1.000

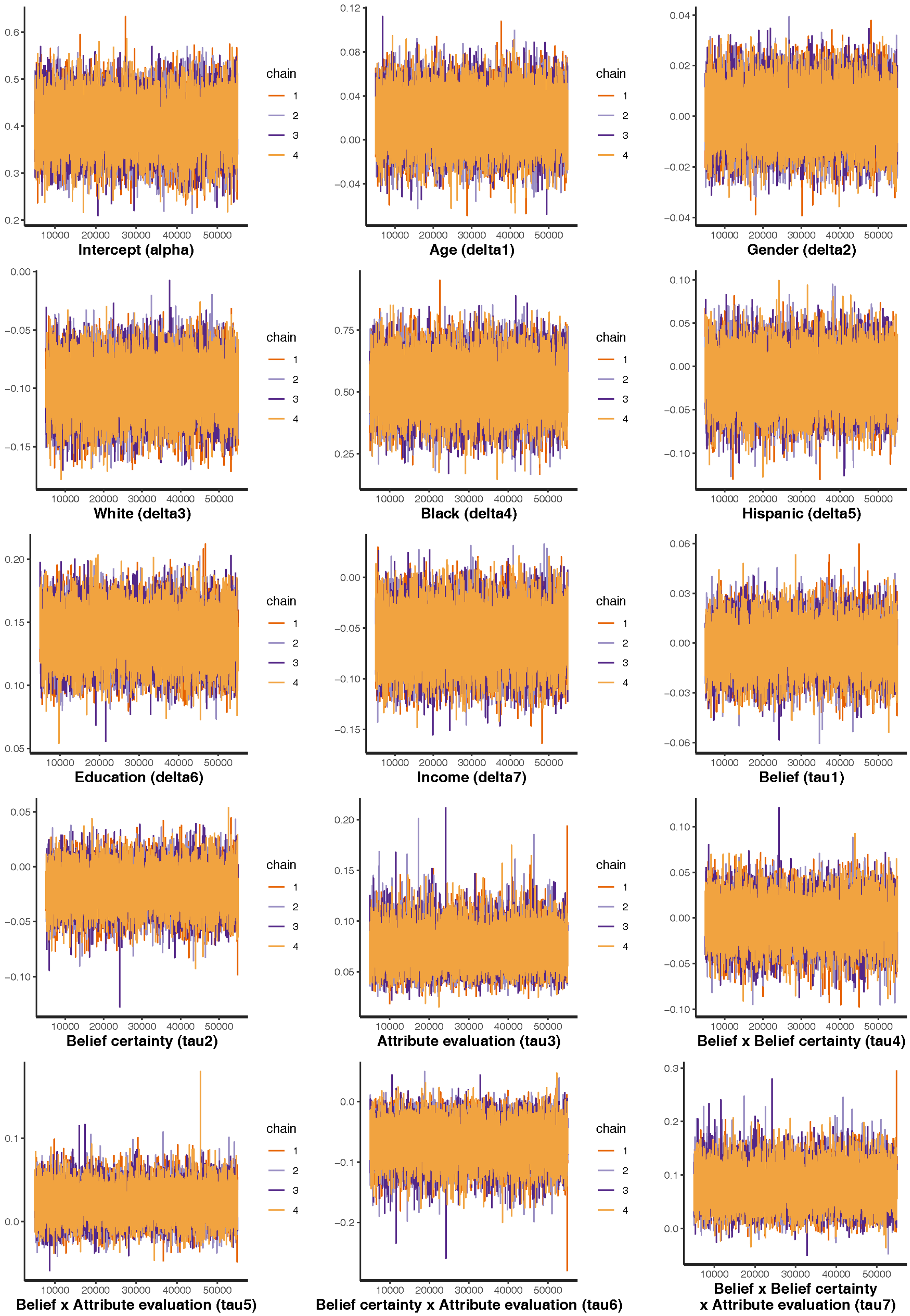

Figure V.1 *Trace Plots for Intercept, Demographics, and Belief-related Variables (Republicans)*

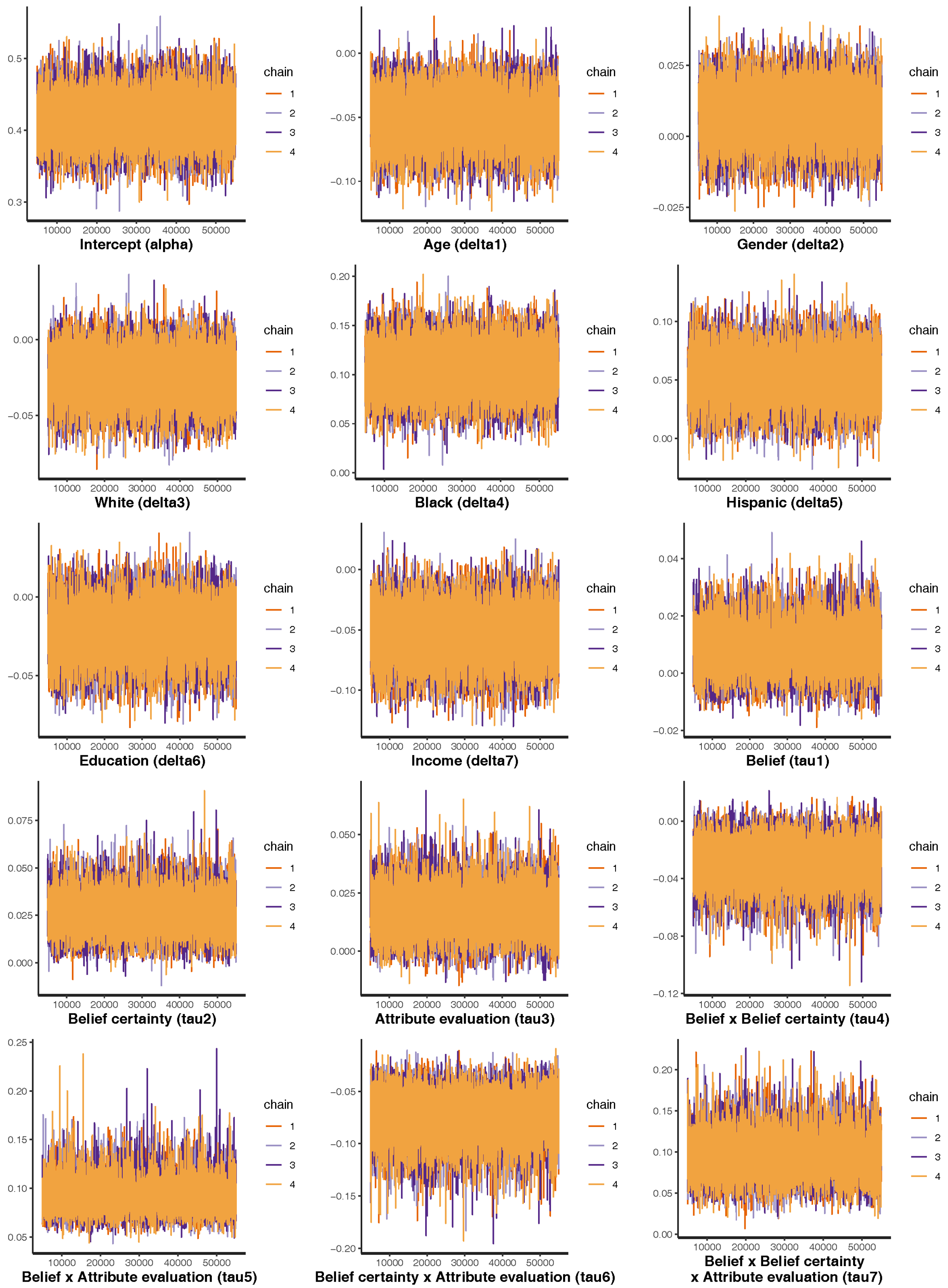

Figure V.2 *Trace Plots for Intercept, Demographics, and Belief-related Variables (Independents)*

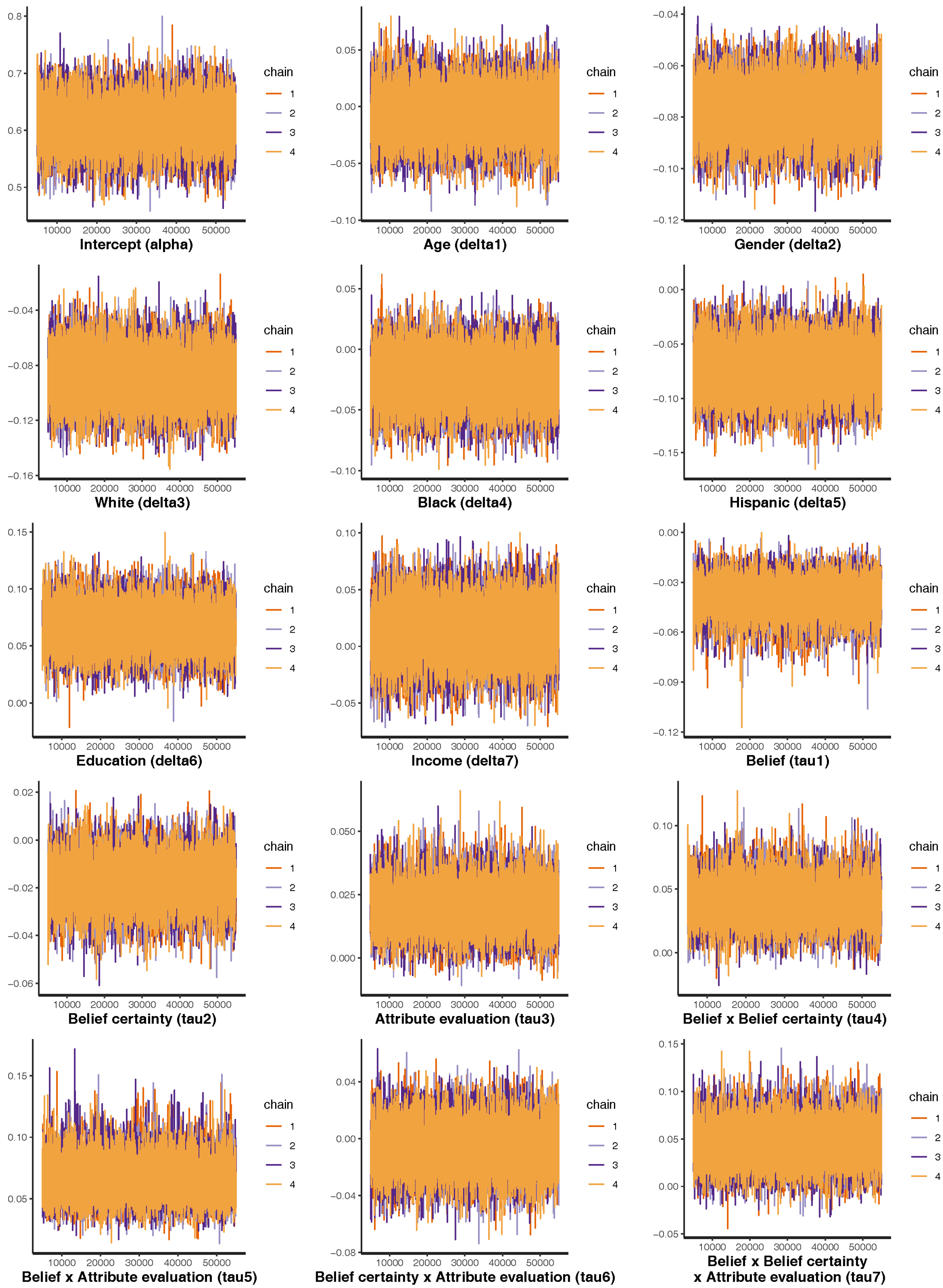

Figure V.3 *Trace Plots for Intercept, Demographics, and Belief-related Variables (Democrats)*

APPENDIX VI

Full Parameter Estimates of Provision Importance by Partisan Groups

Table VI.1 *Bayesian Estimation of Provision Importance (Republicans)*

	Mean	95% HDI
Death panel (ω_1)	.450	[.199, .737]
Drug companies fee (ω_2)	.069	[.002, .228]
Individual mandate (ω_3)	.728	[.489, .957]
Make insurance for sale (ω_4)	.352	[.109, .620]
Subsidize low income (ω_5)	.879	[.649, .996]
ID Card (ω_6)	.124	[.007, .309]
Undocumented immigrants free (ω_7)	.861	[.616, .995]
Insurance companies fee (ω_8)	.153	[.007, .404]
No dropped coverage (ω_9)	.035	[.001, .123]
No capped coverage (ω_{10})	.082	[.003, .228]
Cover under 26 (ω_{11})	.194	[.031, .394]
No preexisting condition denial (ω_{12})	.098	[.005, .266]
Employer must provide (ω_{13})	.333	[.136, .562]
Subsidize seniors (ω_{14})	.037	[.001, .132]
Smoker fee (ω_{15})	.064	[.002, .208]
Soda tax (ω_{16})	.027	[.001, .098]
Small business tax credits (ω_{17})	.072	[.002, .234]
Disclose illness to employers (ω_{18})	.106	[.004, .308]

Table VI.2 *Bayesian Estimation of Provision Importance (Independents)*

	Mean	95% HDI
Death panel (ω_1)	.709	[.484, .931]
Drug companies fee (ω_2)	.288	[.083, .517]
Individual mandate (ω_3)	.908	[.704, .997]
Make insurance for sale (ω_4)	.067	[.003, .202]
Subsidize low income (ω_5)	.081	[.004, .223]
ID Card (ω_6)	.019	[.001, .070]
Undocumented immigrants free (ω_7)	.615	[.398, .849]
Insurance companies fee (ω_8)	.663	[.424, .914]
No dropped coverage (ω_9)	.132	[.009, .309]
No capped coverage (ω_{10})	.232	[.068, .423]
Cover under 26 (ω_{11})	.425	[.254, .611]
No preexisting condition denial (ω_{12})	.103	[.006, .254]
Employer must provide (ω_{13})	.290	[.131, .470]
Subsidize seniors (ω_{14})	.224	[.055, .413]
Smoker fee (ω_{15})	.041	[.001, .136]
Soda tax (ω_{16})	.063	[.002, .197]
Small business tax credits (ω_{17})	.801	[.553, .985]
Disclose illness to employers (ω_{18})	.097	[.004, .259]

Table VI.3 *Bayesian Estimation of Provision Importance (Democrats)*

	Mean	95% HDI
Death panel (ω_1)	.128	[.005, .383]
Drug companies fee (ω_2)	.087	[.002, .289]
Individual mandate (ω_3)	.718	[.471, .956]
Make insurance for sale (ω_4)	.039	[.001, .139]
Subsidize low income (ω_5)	.190	[.015, .444]
ID Card (ω_6)	.754	[.481, .977]
Undocumented immigrants free (ω_7)	.502	[.263, .769]
Insurance companies fee (ω_8)	.417	[.097, .778]
No dropped coverage (ω_9)	.536	[.184, .908]
No capped coverage (ω_{10})	.896	[.673, .997]
Cover under 26 (ω_{11})	.767	[.479, .983]
No preexisting condition denial (ω_{12})	.191	[.015, .451]
Employer must provide (ω_{13})	.150	[.008, .373]
Subsidize seniors (ω_{14})	.056	[.002, .188]
Smoker fee (ω_{15})	.460	[.126, .834]
Soda tax (ω_{16})	.078	[.002, .272]
Small business tax credits (ω_{17})	.610	[.290, .930]
Disclose illness to employers (ω_{18})	.045	[.001, .168]

APPENDIX VII

RStan Coding for Counterfactual Simulations using Bayesian Linear Regression Models

```
data {
 int<lower = 0> N; //number of respondents
 int<lower = 0> J; //number of coefficients per provision
 int<lower = 0> I; //number of provisions
 int<lower = 0> D; //number of demographic covariates
 matrix[N, I*J] x; //provision predictors matrix
 matrix[N, I*J] x1; //baseline scenario predictors matrix
 matrix[N, I*J] x2; //all correct scenario predictors matrix
 matrix[N, I*J] x3; //fully certain scenario predictors matrix
 matrix[N, I*J] x4; //optimal scenario predictors matrix
 matrix[N, D] d; //covariate predictors matrix
 vector[N] p; // partisanship
 vector[N] y; // overall attitude—linear
}
parameters {
 real alpha; //intercept
 real gamma; // partisanship coefficients
 vector[D] delta; //demographic covariates coefficients
 vector[J] tau; //provision predictors coefficients
 vector<lower = 0, upper = 1>[I] omega; //estimated provision importance (informative prior)
 real epsilon; // error term
}
transformed parameters {
 vector[I*J] lambda; //structural constraints (informative prior)
  for (j in 1:J){
   for (i in 1:I){
    lambda[I*(j-1)+i] = omega[i] * tau[j]
  }
 }
}
model {
 y ~ normal(alpha + lambda * x + gamma * p + delta * d, epsilon); //likelihood function
}
```

```
generated quantities {
 vector[N] y1; //predicted attitude—linear (baseline)
 vector[N] y2; //predicted attitude—linear (all correct)
 vector[N] y3; //predicted attitude—linear (fully certain)
 vector[N] y4; //predicted attitude—linear (optimal)
for (n in 1:N) {
 y1[n] = normal_rng(alpha + lambda * x1[n] + gamma * p + delta * d, epsilon);
 };
for (n in 1:N) {
 y2[n] = normal_rng(alpha + lambda * x2[n] + gamma * p + delta * d, epsilon);
 };
for (n in 1:N) {
 y3[n] = normal_rng(alpha + lambda * x3[n] + gamma * p + delta * d, epsilon);
 };
for (n in 1:N) {
 y4[n] = normal_rng(alpha + lambda * x4[n] + gamma * p + delta * d, epsilon);
 }
}
```

APPENDIX VIII

RStan Coding for Counterfactual Simulations using Bayesian Logistic Regression Models

```
data {
 int<lower = 0> N; //number of respondents
 int<lower = 0> J; //number of coefficients per provision
 int<lower = 0> I; //number of provisions
 int<lower = 0> D; //number of demographic covariates
 matrix[N, I*J] x; //provision predictors matrix
 matrix[N, I*J] x1; //baseline scenario predictors matrix
 matrix[N, I*J] x2; //all correct scenario predictors matrix
 matrix[N, I*J] x3; //fully certain scenario predictors matrix
 matrix[N, I*J] x4; //optimal scenario predictors matrix
 matrix[N, D] d; //covariate predictors matrix
 vector[N] p; // partisanship
 array[N] <lower = 0, upper = 1> y; //overall attitude—binomial
}
parameters {
 real alpha; //intercept
 real gamma; // partisanship coefficients
 vector[D] delta; //demographic covariates coefficients
 vector[J] tau; //provision predictors coefficients
 vector<lower = 0, upper = 1>[I] omega; //estimated provision importance (informative prior)
}
transformed parameters {
 vector[I*J] lambda; //structural constraints (informative prior)
  for (j in 1:J){
   for (i in 1:I){
    lambda[I*(j-1)+i] = omega[i] * tau[j]
  }
 }
}
model {
 y ~ bernoulli_logit(alpha + lambda * x + gamma * p + delta * d); //likelihood function
}
generated quantities {
```

```
 array[N] <lower = 0, upper = 1> y1; //predicted attitude—binomial (baseline)
 array[N] <lower = 0, upper = 1> y2; //predicted attitude—binomial (all correct)
 array[N] <lower = 0, upper = 1> y3; //predicted attitude—binomial (fully certain)
 array[N] <lower = 0, upper = 1> y4; //predicted attitude—binomial (optimal)
for (n in 1:N) {
 y1[n] = bernoulli_logit_rng(alpha + lambda * x1[n] + gamma * p + delta * d;
};
for (n in 1:N) {
 y2[n] = bernoulli_logit_rng(alpha + lambda * x2[n] + gamma * p + delta * d;
};
for (n in 1:N) {
 y3[n] = bernoulli_logit_rng(alpha + lambda * x3[n] + gamma * p + delta * d;
};
for (n in 1:N) {
 y4[n] = bernoulli_logit_rng(alpha + lambda * x4[n] + gamma * p + delta * d;
}
}
```

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