

The Dynamic Constraint of Religious Belief Systems^{*}

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2021-02-27

Abstract

To what extent does social life constrain a person's attitudes over time, and what facilitates this stability? Existing sociological research varies in the degree to which it suggests that attitudes are constrained, while simultaneously arguing in favor of three principal sources of constraint: organizations, social networks, and cultural schema. This paper makes three contributions to these debates. First, I argue that rather than think of constraint as evident in pairwise relationships between attitudes at a single point in time, as many existing measures do, constraint should be thought of as restrictions on which attitudes people feel like they can give over time. Second, I use Latent Class Analysis to derive five belief systems that differently constrain religious, family, and moral beliefs in the National Study of Youth and Religion and show that the variance in responses within groups at the survey's second wave strongly predict how much people change their responses over time, as well as which responses they give. Third, I adjudicate between cultural-schematic, organizational, and social network sources of attitude structuring, showing that as people change their organizational and social contexts, their beliefs remain more stable than these changes would imply, suggesting that belief structures are organized early in life and shape people's beliefs and behaviors over time.

1 Introduction

A key way the social world is assumed to shape individual behavior is by constraining people's understanding of which attitudes, beliefs, and behaviors are compatible (???). It is through this process that society is assumed to get "into the heads" of people and reproduce itself (???), create patterns of attitude association in the population (Rawlings 2020; DellaPosta 2020; Goldberg and Stein 2018), and shape behaviors and affiliation over time (Vaisey 2009).

In his review paper on culture and cognition, DiMaggio suggests that a contemporary understanding of human cognition "directs the search for sources of stability and consistency in our

^{*}Thanks to Craig Rawlings, Christopher Johnston, and Nicholas Restrepo Ochoa for feedback on a very early, very different draft of this paper.

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beliefs and representations, first, to schematic organization, which makes some ideas or images more accessible than others; and, second, to cues embedded in the physical and social environment” (??? p. 267). The first of these pieces suggests that culture, internalized as shared cognitive structures, shapes how people process, store, and recall information in ways that facilitate stable lines of action over time [(???);]. The second posits that social environments – organizations, institutions, and social networks – constrain people’s understandings of which attitudes and behaviors are related and keep certain attitudes at the forefront of people’s attention (???; Goldberg and Stein 2018).

In sociology, work highlighting the influence of social and physical structures on attitude structure has been quite successful (Martin 2002; Rawlings 2020), but work showing the relative role of cognitive-cultural structures in producing stability is quite rare, and a conclusion across the social sciences has been that people’s cognition, in general, is not strongly constrained by these cultural-cognitive structures (Converse 1964; Zaller 1992).

This is due in part to the challenges of measuring these cultural-cognitive structures. Measures of attitude structuring have tended to focus, in one form or another, on the pairwise relationship between survey responses in cross-sectional data (Baldassarri and Gelman 2008; Baldassarri and Goldberg 2014; Boutyline and Vaisey 2017; Goldberg 2011; Hunzaker and Valentino 2019; Martin 2002). This work has led to numerous insights into the structuring of political and cultural thought in different groups, heterogeneity in belief patterns, and the social factors that give rise to constrained thinking. But there are two problems with these approaches as they pertain to measuring cultural-cognitive structuring.

First, decades of research in cultural sociology and public opinion research find that people do not have *an* attitude on a topic. Instead, they have a range of considerations shaped by culture and personal experience (Swidler 1986, 2001 @zaller1992). Because people often hold contradictory considerations, and because which considerations influence cognition at any time can be shaped by local circumstances, attitudes as measured by surveys often appear to change substantially over time (Converse 1964). If the assumption of measuring cultural-cognitive structures is that the over-time relationships between survey responses do not change, this movement suggests that cognition is not

structured.

However, the theory of cultural cognition says that schmatic structures organize people's underlying considerations, not necessarily their manifest survey responses (???; ???). Under this framework, schematized networks of considerations should *probabilistically* produce certain lines of behavior such as survey responses, but these will be subject to local influences. Shared networks of considerations do not have to produce shared attitudes at a single point in time. If two people have similar (culturally shaped) schema that connect diverse and contradictory considerations, this can result in similar instability over time.

The second major challenge of this approach is apparent in the central metaphor these researchers use to explain attitude constraint: movement. Across these works, the structuring of attitudes is consistently described as limitations on the movement of attitudes over time, but it is rarely tested using within-person, over-time data (for an exception, see Rawlings 2020). In using static measures of constraint, researchers tend to assume that because people hold two ideas at the same time or because beliefs covary in the population, people understand these ideas as related and constraining. But co-occurrence and co-variance in static data does not prove the cognitive linkages or the presence of constraint that these researchers tend to assume (J. L. Martin 2000). The clustering of people in social groups with distinct attitudes could be driven by a number of processes besides cognitive linkage, such as social influence or selection (Lewis and Kaufman 2018; Vaisey and Lizardo 2010).

Because measuring culturally structured beliefs has proven so difficult, evidence that organizational and social influences shape and constrain attitudes have tended to dominate explanations of the social structuring of attitudes over explanations of cultural background. At the same time, people's dispositions across a range of topics appear to be much more stable over time than would be predicted based on people's movement across contexts, suggesting that some cultural structuring likely occurs early in the life course (Kiley and Vaisey 2020; Vaisey and Miles 2017).

In this paper, I attempt to reconcile these conceptual and methodological issues by rethinking the empirical signature of a belief system. I make three principal contributions. First, drawing on insights from sociology of culture and cognition, the social psychology of attitude development,

and political psychology, I argue that the cultural/cognitive variant of attitude structuring is not well demonstrated by attitude clustering at a single time, measures of relationships between attitudes at a single time, or even pairwise change over time. Instead, a belief system should be conceptualized as a set of considerations that results in a restriction (or lack of restriction) on which responses a person feels they can give over time. Rather than assume competing belief systems constrain similar beliefs, I argue that belief systems vary in how extensive they are – the number of beliefs they constrain – as well as how intensive they are – the degree to which they constrain different beliefs.

Second, given this model of a belief system, I argue that Latent Class Analysis – a method of data reduction that groups people into classes with similar probabilities of giving different responses to particular questions – reflects the theoretical tenets of this kind of belief system better than many existing measures designed to tap attitude structuring, such as pairwise correlation, relational class analysis, and correlational class analysis (Converse 1964; Goldberg 2011; Boutyline 2017). I argue that the constraints evident within classes at a single point in time should predict the degree to which people change their attitudes over time. I test this proposition using data on religious, moral, and family-structure beliefs from the National Study of Youth and Religion. Latent class analysis identifies five belief systems. These systems vary in the number of beliefs they constrain, the degree to which they constrain beliefs, and the portions of belief space they constrain respondents to. I show that the constraints evident in cross-sectional data at the survey's second wave predict which attitudes people change between waves and how they change them better than competing models of attitude formation.

Third, I adjudicate the relative importance of these cultural-cognitive belief systems and structural influences such as organizational participation and social networks on the pattern of changes in attitudes over time. I show that belief systems observed at the second wave of the NSYR better predict the pattern of attitude changes over time than models accounting for changing social circumstances.

The results have several implications. First, they suggest that cultural background plays a strong role in shaping the underlying cognitive structures that influence which attitudes people feel

they can give over time, but that this manifests differently than how researchers tend to assume constraint works. Second, they show that modeling beliefs as a multinomial draw from a belief space provides a good fit to the observed pattern of attitude behavior over time, suggesting that conceptualizing attitudes as probabilistic manifestations of underlying consideration sets is a good fit to how they behave in the real world. Finally, these results show that the social circumstances in which people develop attitudes during the adolescence and early adulthood appear to be highly influential in shaping their cognition as they move across social environments, while changes in these social environments are less influential. It is not that organizations and social networks lack importance; it is that these influences matter strongly early in the life course and less later in life, at least with respect to the beliefs measured here.

2 Theoretical Framework

2.1 What Are Attitudes?

Understanding the empirical signature of a belief system in survey data must start with a model of the behavior of attitudes and survey response. A key finding from decades of work in cultural sociology and public opinion is that people consume diverse and contradictory bits of culture, often storing this heterogeneous mixture without taking time to reconcile its contradictions (Martin 2010; Swidler 1986; Zaller 1992). Without strong motivation to reconcile conflicts, people have a hard time keeping conflicting considerations out of their heads (Martin 2010; Zaller 1992). As a result, “our heads are full of images, opinions, and information, untagged as to truth value, to which we are inclined to attribute accuracy and plausibility” (DiMaggio 1997: p. 267). In their day-to-day lives, people seem to have no trouble believing that “love is (1) a clear, all-or-nothing choice; (2) of a unique other; (3) made in defiance of social forces; and (4) permanently resolving the individual’s destiny” while simultaneously believing that “(1) Real love is not sudden or certain ... (2) There is no ‘one true love’ ... (3) The kind of love that leads to marriage should not depend on irrational feeling in defiance of social convention ... [and] (4) Love does not necessarily last forever” (Swidler 2001: pp. 113-114), despite the inherent

contradictions in these sentiments.

This heterogeneity of considerations has consequences for survey response over time. When asked to give an opinion on an issue, people seem to sample from the range of considerations stored in their heads, shaped by local influences such as question structure and wording, as well as recent stimuli such as discussions with peers or the news, and generate an opinion on the basis of these stored considerations and short-term influences (Swidler 2001; Zaller 1992). People with conflicting considerations do not simply average their considerations and pick scale midpoints (though they do this occasionally), but they can range widely in their beliefs over time as local influences shift. This behavior is evident in interviews, where people tend to draw on diverse considerations to explain or justify behavior, often contradicting themselves (Swidler 1986, 2001). It is also evident in people's responses to the same survey question over time, where they vacillate between ends of scales much more frequently than we would expect if they were stable opinion holders (Zaller 1992; Converse 1964).

At the same time, not all people display this level of ambivalence. On any particular question, some proportion of the population does clearly articulate the same opinions over time, with people differing on which issues they are stable (Converse 1964; Hill and Kriesi 2001). And social behaviors affect attitude stability, suggesting that variation is not simply attributable to measurement error. In politics, people who pay more attention to political news tend to be much more stable on their attitudes over time than people who do not (Converse 1964; Freeder, Lenz, and Turney 2019; Zaller 1992). Other work shows that the presence of cognitive authorities in small communities facilitates the structuring of attitudes over time (Martin 2002; Rawlings 2020). And work in cultural sociology suggests that attitudes can predict behaviors and patterns of affiliation over time (Vaisey 2009; Vaisey and Lizardo 2010), which we would not expect if attitudes were temporary constructs shaped exclusively by local circumstances.

In general then, it is wrong to say that people have *an* attitude about something measured in a survey. What they have is a set of considerations that might point toward giving the same response over time or a set of considerations that might cause them to shift around in response to local changes,

or something in between. Any single response will be a draw from this consideration set with more or less random error shaped by personal circumstances at any time. For example, a person might have the heterogeneous and conflicting models of love that Swidler (2001) documents. When asked if unhappy couples should get divorced, this person could give either answer depending on which considerations are foremost in their mind. If something has triggered the prosaic model of love, the person might say that people should get divorced if they are unhappy. If something has triggered the romantic model of love, the person might oppose divorce.

2.2 Sources Belief Structuring

If public culture is heterogeneous and conflicting, and if people tend to internalize bits of culture uncritically, how do we explain the fact that some people demonstrate remarkable consistency in their attitudes over time and the fact that that different kinds of attitudes often predict behavior (Miles 2015; Vaisey 2014)? There are two principal explanations in sociology: one cultural, and one structural (DiMaggio 1997: p. 267).

The cultural explanation for attitude stability posits that people's attitudes are shaped by cognitive structures called schema, "knowledge structures that represent objects or events and provide default assumptions about their characteristics, relationships, and entailments under conditions of incomplete information" [DiMaggio (1997); p. 269]. In cultural sociology, schema are conceptualized as connections of concepts, generated through repeated exposure, that shape how people process information.

While schema can be idiosyncratic, many are shared or cultural. Because they are assumed to form through the repeated exposure, they tend to reflect institutionalized social structures, which then facilitate many people developing similar cognitive structures, thereby reproducing these cultural structures. Schema then shape the interpretation and recall of information, shared interpretation of cultural objects, and patterns of interaction, all shaping the patterns of attitudes people exhibit over time (DiMaggio 1997; ???; Hunzaker 2016; Rawlings and Childress 2019). Uncovering these relationships between concepts are often the principal goal of methods designed to measure culture

(Hunzaker and Valentino 2019; Goldberg 2011; Boutyline 2017; ???).

In this framework, people demonstrate stable attitudes because their cultural-cognitive schema prevent the internalization of schema-inconsistent information and facilitate the storage and recall of schema-consistent information across social settings (Hunzaker 2016; Hunzaker and Valentino 2019). A person who believes in an all-powerful God who deems divorce antithetical to eternal salvation – a set of connections in the underlying belief structure – is going to have an easier time consistently giving the same response to a question about whether divorce is acceptable than someone who has internalized Swidler's heterogeneous models of love. But people might also demonstrate inconsistency when schematic structures point to conflicting outcomes. This might be because schematic structuring is weak preventing the rejection of heterogeneous information and making attitudes susceptible to short-term influences (Martin 2010). But strong schematic structure can also produce inconsistency if it is misaligned with a question. A question asking whether Jesus Christ was a man or God might prove problematic for the most structured Christian belief system (???), but not very challenging for an atheist.

The principal alternative explanation for attitude stability argues that social structures – organizations and social networks – facilitate attitude stability across the life course. Under this framework, people's attitudes and beliefs are principally shaped by social influence and by the scaffolding provided by organizational structures (???; Martin 2002; Rawlings 2020).

In this framework, people maintain consistency because they consistently hear a single line of cultural reasoning and rarely hear heterogeneous or conflicting information (Zaller 1992). Cognitive authorities, leaders endowed with the social responsibility for shaping beliefs, provide clear guidelines for what attitudes go together, and organizational hierarchies make certain belief structures appear impossible (Martin 2002). Affectively laden social interactions can make holding some attitudes feel uncomfortable, leading people to change their attitudes (???; Rawlings 2020). Physical features of the social environment consistently facilitate the recall of certain beliefs. These explanations do not require any durable cognitive structuring, simply short-term representations repeatedly reinforced by the local environment.

To some extent attitude stability likely reflects a dynamic interplay between cultural-cognitive structures and social structures (Lizardo and Strand 2010; Martin 2010). And adjudicating the relative influence of these processes is difficult because people's cultural beliefs and preferences appear to shape their social networks and their organizational participation (Lizardo 2006; Lewis and Kaufman 2018; Vaisey and Lizardo 2010). But research in the social sciences has tended to focus on using social structures to explain stability and change in behavior. A key reason for this is because measuring cultural belief structures in people has proven challenging, while measuring social structures have proven easier. Without a clear measure of a belief structure, there is no way to adjudicate the relative influence of these cognitive representations on attitudes over time.

2.3 Measures of Attitude Structures

The most common approach to measuring belief structures in the social sciences focuses on the pairwise relationships between survey items in cross-sectional data, typically using covariance or correlation (Baldassarri and Gelman 2008; Boutyline and Vaisey 2017; Converse 1964; DellaPosta, Shi, and Macy 2015). Related measures designed to address measurement error in individual responses (Ansolabehere, Rodden, and Snyder 2008) still tend to look at the pairwise relationship between latent beliefs.

These correlational models rest on what I call the “diametric assumption” that beliefs are structured or constrained when they covary across people, that people who are high on attitude are high on a second, while people who are low on one attitude are low on the second. While this is good evidence for a static variation of constraint – that two issues tend to cluster in the population – it is not necessarily indicative of the schematic organization of considerations in people's heads. Under this logic, if liberals and conservatives hold opposite positions, then they are assumed to understand a link between them, even if they, in their own heads, do not. Similarly, if they do not have opposite positions, neither is assumed to be constrained in their thinking, even if members of both groups subjectively understand their belief system to imply that position (the theoretical definition of the cognitive version of constraint). But there are often times when different belief systems constrain

people to the same position in belief space. For example, all varieties of American popular nationalism uncovered by Bonikowski and DiMaggio (2016) restrict people to some level of agreement that it is important for Americans to have American citizenship and some level of pride in the Armed Forces. No form rejects these, saying that Americans should not have U.S. citizenship, but that does not make these unconstrained forms of thought.¹

A more recent development in schema measurement are relational and correlational class analysis methods, which attempt to partition samples into groups that have similar patterns of relationships among beliefs, allowing for heterogeneous and non-oppositional belief systems in the same population (Goldberg 2011; Boutyline 2017). However, the diametric assumption still underlies interpretation of these methods. If people are located in opposite positions, researchers employing these methods assume that people see the same “logic” of a space. For example, Baldassarri and Goldberg assume that “a high-earning and secular Manhattan lawyer, squeezed by her progressive leanings on moral issues and her support for fiscal austerity” and “a working-class devout churchgoer torn between his moral conservatism and redistributive economic interests” see politics through the same logic, though this might not be true (Baldassarri and Goldberg 2014: p. 46). In fact it is hard to imagine that these people see political conflict as an opposition between “libertarian” thought on one hand and “populist” thought on the other, when the main political parties align orthogonal to this axis. What is more plausible is that these people’s views are simply unconstrained by the liberal-conservative paradigm, not exhibiting a separate “logic” of the space.

These methods, as well as measures based on entropy (???), face three other major challenges. First, as discussed above, the schematization of cognition takes place well below the level of survey responses, in connections between concepts and representations, not in connections of attitudes. As Hunzaker and Valentino (???) show, people with very similar schema frequently produce

¹This fallacy, assuming that Belief 1 is associated with Belief 2 only if Belief 1’s opposite is associated with Belief 2’s opposite, is also called “denying the antecedent” or the “fallacy of the inverse,” and should be familiar to social scientists. Avoiding this problem is the reason classical statistical tests in the social sciences have the structure they do: rejecting a null hypothesis rather than affirming an alternative hypothesis, since there are always other things that could cause an outcome. The statement $P \rightarrow Q$ (if conservative, then oppose abortion) only implies one conclusion (the contrapositive), $\neg Q \rightarrow \neg P$ (if not oppose abortion, not conservative). It does not imply the inverse, $\neg P \rightarrow \neg Q$ (not conservative, not oppose abortion).

different answers to the same attitude question. Schema are connections of concepts that probabilistically produce lines of action and can produce inconsistency if they connect conflicting concepts and considerations. This means that measuring belief systems as networks of connections between survey responses becomes hard to justify. In any survey wave, people might be presenting one of several answers that does not truly reflect the breadth of their considerations, which is also a product of the schematic structuring of considerations.

Second, these approaches all fail to connect the method of measuring belief structuring with the core theoretical implication of a belief system: constraints on change. These authors all repeatedly invoke the imagery of movement to explain what a belief system is (emphasis added in all):

- “However, these beliefs are still tightly connected, in that *movement* in one implies *movement* in the other” (Martin 2002: p. 868). “Tightness, as defined above, can be interpreted as the imposition of *rules of movement* within the belief space (think of the difference between the constrained motion of driving on surface streets and the unconstrained motion of four-wheeling on the beach). Consensus, on the other hand, can be interpreted as a gross *inability to move away from* some privileged areas of the belief space toward others (without channeling in particular directions whatever degree of *motion* is allowed)” (Martin 2002: p. 874).
- “we might best see the distribution of people in this space as giving us clues about the *rules of motion* in the belief space. If one were to take a picture of some well populated area from a low-orbiting satellite, and marked a spot wherever there was a car, one would be able to figure out rather well where the roads were, and where cars were allowed to go. It is these analogous *rules of movement* that will give us clues as to the nature of social cognition” (J. L. Martin 2000: p. 11).
- “Culture, in this context, can be understood as the unspoken set of rules that tie beliefs together by restricting *movement* in this space along certain axes, which demarcate different social worlds” (Goldberg 2011: p. 1403).
- “We therefore interpret different *axes of movement in a belief space* ... as the empirical signature of ideological constraint” (Baldassarri and Goldberg 2014: 59).

- “attitudes toward science and religion *move* in tandem” (DiMaggio et al. 2018: p. 40).

These researchers understand constraint to be a dynamic phenomenon, but in these studies dynamics are inferred from a snapshot and, importantly, not tested over time. Because people are arrayed along a diagonal in belief space, they are assumed to only travel along this diagonal (Martin 2002; Baldassarri and Goldberg 2014). Because people are clustered in portions of the belief space, they are assumed not to move from one cluster to another. These might not be unreasonable assumptions, but they are assumptions that are not tested.

Finally, because these measures of belief systems do not make clear predictions for the behavior of attitudes over time, it is hard to assess their validity and compare their influence to other competing influences. While they identify structuring of the population’s beliefs at a single point in time, they do not truly make predictions for how attitudes will change over time, especially in the absence of knowledge about people’s *other* beliefs at a later time. In fact, their assumptions seem to imply that beliefs that are constrained do not change (or change in very specific ways), which is undermined by the high degree of variance in people’s attitudes over time (Converse 1964; Zaller 1992).

3 Rethinking Belief Systems

The preceding discussion suggests that cultural belief structures should be thought of as shared sets of considerations (concepts, representations, etc.), and schematic connections between them, that *probabilistically* produce lines of action such as survey responses. These structures thereby limit (or do not limit) people’s responses to certain portions of the belief space over time, but they might not manifest as the same response in each wave. A system might shape people’s considerations by directly providing them (“marriage is good”); by linking considerations together (“god exists says that marriage is important for eternal salvation”); by linking considerations to social groups (“getting married is an important part of being a member of this community”); or by linking considerations to identity (“to be a good Christian, I need to get married”). In doing these things, belief systems shape the

range of messages people receive, the ease with which they can accept or reject other messages they are exposed to, and their ability to recall considerations over time.

In this sense, belief systems reflect “some process whereby the arbitrary movement of individuals in this space has been reined in; more exactly, it may be thought of as the most general introduction of form to an otherwise formless distribution” (J. K. Martin, Pescosolido, and Tuch 2000: p. 865).

Figure XXX presents two hypothetical belief systems. Two panels of the figure represent to two people in the population with different belief systems. The columns reflect the proportion of times they give each answer to two binary questions – one about whether divorce is acceptable and one about whether God exists – assuming we sampled them an infinite number of times under slightly different circumstances. The first system reflects a strong Christian belief system that makes marriage a sacrament and indissoluble. Because the system strongly links marriage to the existence of a deity and eternal salvation, people have a relatively easy time rejecting competing considerations they hear from the environment. A crisis of faith or actual error in filling out the survey might lead him to say that God does not exist at certain time points, but he is expected to enact a fairly consistent line of action over time.

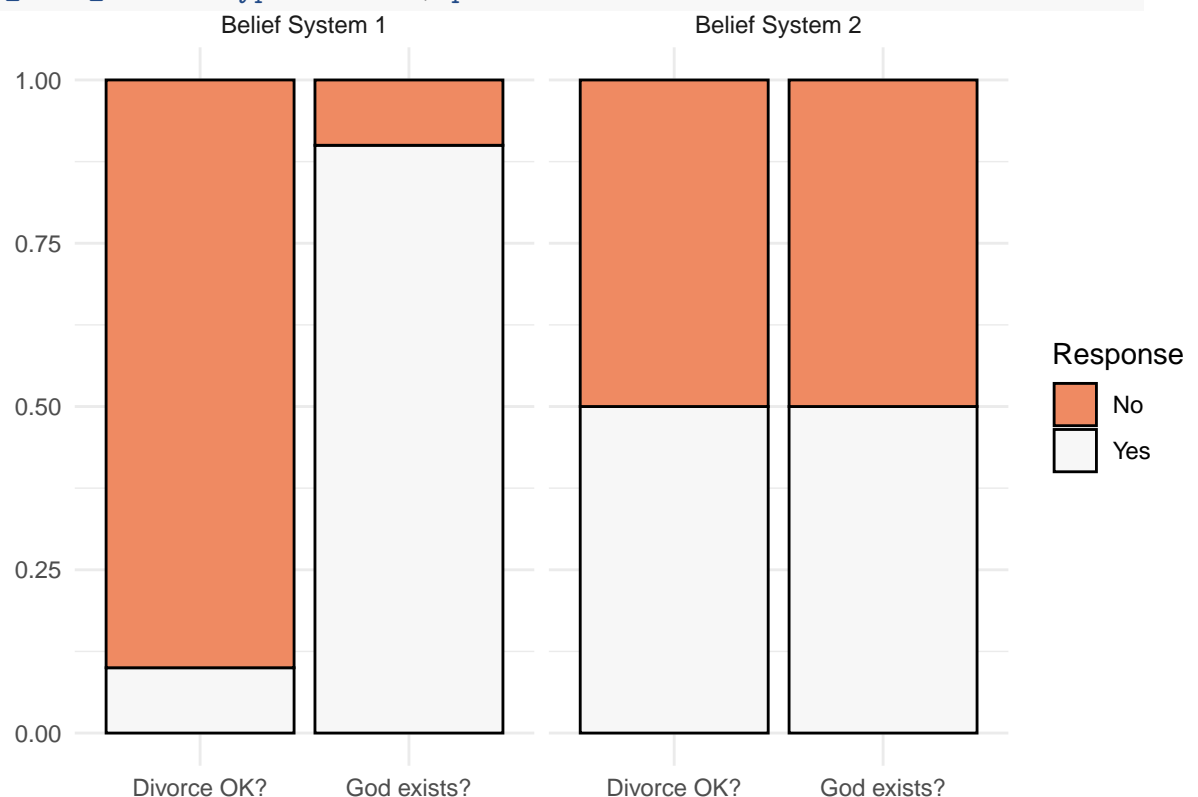
The second system reflects a heterogeneity of considerations present in contemporary American culture. People in this group internalize heterogeneous messages on both dimensions and, as a result, vacillate on both questions over time local influences trigger.

An important point here is that the lack of constraint in the second system is still a reflection of culturally shared schema. Constraint is often assumed to be the signature of a belief system, but it is only one potential empirical manifestation of structured cognition. A schematic system that connects marriage to conflicting prosaic and romantic models of love is still a shared cultural belief system (perhaps the most-shared cultural system we have for love), reflected in the structure of cognition. In other words, inconsistency can be as much a product of cognitive structuring as consistency.

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data.frame(q = c(rep("God exists?", 4), rep("Divorce OK?", 4)),
           group = c(1,1,2,2,1,1,2,2),
           resp = rep(c("Yes", "No"), 4),
           prob = c(.9, .1, .5, .5, .1, .9, .5, .5)) %>%
  mutate(group = recode(group, "1"="Belief System 1", "2"="Belief System 2")) %>%
  ggplot(aes(x = q, y = prob, fill = resp)) +
  geom_bar(stat = "identity", position = "stack", color = "black") +
  facet_wrap(~group) +
  theme_minimal() +
  labs(x = "", y = "", fill = "Response") +
  scale_fill_brewer(type = "div", palette = 5)

```



Belief systems, then, shape the different responses that people give over time and the probability that they give these different responses over time. They might constrain beliefs to some portion of the belief space, but they might not. They might explicitly or implicitly tie beliefs together, but they

might not. They become cultural when they recur across people.

In this framework, then, a cultural belief system is detectable if we see groups of people who have the same probability of answering a question in a particular way over time. The obvious challenge of this approach is that we do not frequently observe people's responses to the same question repeatedly over time, with many panels of attitudes stopping at three waves. Fortunately, a method for detecting such systems in cross-sectional data exists and has been used in sociological studies of attitude structuring before (Bonikowski and DiMaggio 2016; DiMaggio et al. 2018).

4 Latent Class Analysis and Belief Systems

Latent Class Analysis is a data-reduction method that seeks to group people into unobserved categories where, within these categories, the probability of giving a particular response to a question is independent from the probability of giving responses to other questions. This fundamental assumption, the conditional independence assumption, assumes that once the latent class is identified, each person's response on a particular question is an independent draw from the probabilities of the different responses observed within that group.

If a cultural belief system is a shared set of considerations and the connections between them that probabilistically produce certain responses over time across a range of questions, subject to local influences, as the preceding discussion argues, then latent class analysis should be able to detect these systems in a single wave of data, and the features of these systems observed at one time point should be predictive of behaviors over time.

In cultural sociology, DiMaggio and colleagues (???) use LCA to deduce belief systems about religion and science from survey responses in the General Social Survey, and Bonikowski and DiMaggio (???) use LCA to deduce varieties of popular nationalism, also in the GSS. However, neither of these works attempt to test the implications of the deduced classes over time.

4.1 Hypotheses

The preceding discussion suggests a set of ... The first are methodological, revolving around the ... to identify ...

4.1.1 Latent Class as a Measure of Belief Systems

... Specifically, the constraints identified in a latent class at one time should predict the degree to which people change their attitudes over time.

Hypothesis 1: Within belief systems, beliefs that are more constrained will demonstrate less change over time than less constrained beliefs.

Hypothesis 2: Across belief systems, the same belief will show less movement over time if it is in a more constrained belief system.

The model outlined above suggests that the belief system at time 1 should not only predict the degree to which attitudes in any particular system will change, but which responses people whose cognition is governed by these belief systems will give over time. The central assertion is that responses at a particular wave should be conceptualized as independent draws from the deduced multinomial distribution. This distribution is shaped by broad culture forces, but which specific response a person gives at any wave will be shaped by (random) local influences. This means that while it will be very hard to predict what any particular person will say in each wave, assuming these draws are independent can give us strong predictions for the overall count of observed patterns over time.

Hypothesis 3: Over time, the responses given by members should represent a multinomial draw from the deduced belief system.

4.1.2 Adjudicating Culture and Structure

The preceding discussion ..., but assuming that the latent class model sufficiently deduces belief systems that align with the theory outlined here, and that the preceding hypotheses are proven correct, identification of the belief system through latent class analysis allows for adjudication of the competing influences of belief systems, organizational structures, and social networks in shaping attitudes

over time.

The fundamental claim of the cultural schema literature is that belief systems, once established, are relatively impervious to outside social influences. If people have structured schematic thinking, they are less susceptible to the influence of alternative considerations that come from changing social environments (???). This might in part be because they ... , but it is also likely ... process new information.

The alternative is that as people move across social space, they hear different sets of considerations that continually reshape their consideration sets and the attitudes they report in surveys. If this is the case, then

Hypothesis 4: Belief systems will better predict people's observed changes better than models using changing social circumstances over time.

5 Data and Measures

5.1 The National Study of Youth and Religion

Data for this analysis comes from waves two through four of the National Study of Youth and Religion, a four-wave panel data set of adolescents that began when respondents were between the ages of 13 and 17 and surveyed them every three or four years for four waves. In wave 2, respondents were between ages 16 and 20, in wave 3 respondents were between ages 17 and 24, and in wave 4 respondents were between ages 20 and 32.

The age range of the NSYR is important to the theoretical argument outlined here as it pertains to the movement across organizational and social contexts. Existing work suggest that adolescence and early adulthood, the period leading up to interviews at Wave 2 and between waves 2 and 3, is a particularly formative period for the cultural schematic cognitive structures that are assumed to shape attitudes and behaviors (Kiley and Vaisey 2020; ???; ???).

The period between wave 2 and wave 3 represents a significant time of transition for young people in the United States, as they move out of their parents homes, into college and the workforce,

began to form long-term romantic attachments, and generally transition from adolescence to adulthood. There is likely more movement across social contexts at this period than most other periods of life. As such, this provides a good window in which to test the competing influences of cultural belief structures, organizational settings, and social change.

Because I do not use data from the first wave of the NSYR,² and because time matters significantly in the testing of the theoretical model outlined above, for clarity I will refer to waves 2, 3, and 4 of the NSYR as times 1, 2, and 3 for the rest of this paper.

5.2 Measures

5.2.1 Beliefs

In times 1 through 3, NSYR respondents were asked a series of questions about their religious, moral, and family-structure beliefs. They include seven questions asking about specific religious beliefs, four questions asking about morality and the role of religion in daily life, and six questions about gender relations and family structures.³ These questions are asked on either three-point scales of “yes,” “maybe,” and “no,” or five-point scales of “strongly agree,” “agree,” “undecided/don’t know,” “disagree,” “strongly disagree.” These variables are outlined in Table XXX.

To make the range of responses to each question comparable, I scale all attitude measures to five-point scales between 1 and 5 by converting questions on three point scales: “yes” to 1, “maybe” to 3, and “no” to 5.

5.2.2 Covariates

I examine three principal sources of attitude structuring: sociodemographic background, organizational participation, and social networks. Sociodemographic background variables include respondent gender (male or female), race (black, white, or other), census division (northeast, south, midwest,

²Some of the attitude measures appear at wave 1, but many do not.

³An obvious omission from this list of questions is the one Vaisey (2009) uses to predict adolescent behavior and social networks over time, which he argues represents people’s “moral typology.” Because of a coding error, responses to that question were lost for almost all respondents at Wave 3.

west) whether at least one parent has a bachelor's degree, parent's income, and whether a two parents were present in the household growing up. Of these, only census division changes meaningfully between waves.

A second set of covariates is designed to tap organizational participation, which is expected to change between waves. I focus on two types of organizations: religious organizations and participation in education systems. Given the role of religious organizations in shaping the attitudes under examination here, I include a set of dummies for the respondents' religious tradition and a measure of church attendance. I also include a variable measuring the number of years of education a person has received above ninth grade.

Finally, to measure social network influence, I include the proportion of a respondents' friends who share that person's religious orientation, including no religious orientation for people who do not express one.⁴ I also include the highest level of closeness a respondent reported with either parent.

These covariates are measured at times 1 and 2. Only some of these questions were asked at time 3. Table XXX presents these covariates.

5.3 Belief Systems

I use Latent Class Analysis to deduce a set of belief systems using the 19 attitude items asked at time 1. Latent Class Analysis attempts to assign a class to each respondent such that their responses are independent from each other within classes. Maximum likelihood estimation is used to .

$$P(Y = y) = \sum_j P(K = j)P(Y = y|K = j)$$

The LCA model estimates the relative class proportions, $P(K)$, and the conditional probabilities of each response as a function of each class.

The LCA model treats responses as nominal, even though they are often assumed to have

⁴Almost all respondents at time 1 (%%%) said they had five close friends.

some underlying latent structure.

, the model includes the covariates outlined above as predictors of class assignment. The model simultaneously estimates two conditional probabilities: the probability of response conditional on group assignment and the probability of group assignment conditional on covariates. I use Bayesian information criterion to select the best-fitting number of classes.

5.4 Testing Hypotheses

5.4.1 Change Over Time

The first two hypotheses make predictions about how much attitudes should change over time as a function of the constraint within a belief system at a single point in time. Within a system, more constrained beliefs should change less over time than less constrained beliefs, and across systems, a belief should change less in a more constrained system.

I measure constraint of a particular attitude, j , for members of a designated belief system, k , by calculating the within-class standard deviation of responses to that attitude. Latent Class Analysis assigns each person a probability of belonging to a each class. I assign people to the class with the highest posterior probability. I then calculate the standard deviation of responses within that group, treating responses as continuous, rather than nominal as the LCA does. A group where most people tend to give the same response or cluster in adjacent responses will have a low standard deviation and therefore demonstrate high constraint. A group where people tend to give answers across the scale will have a high standard deviation and therefore low constraint.

$$\sigma_{jk} = \sqrt{\frac{\sum (x_{ijk} - \mu_{jk})^2}{N_k - 1}}$$

The outcome of interest is the degree to which people actually do change their attitudes over time. I measure within-person variance over time using the within-person standard deviation of responses given at times 1, 2, and 3.

$$\sigma_{ij} = \sqrt{\frac{\sum (x_{ijt} - \mu_{ij})^2}{N_{it} - 1}}$$

I test the first and second hypothesis using a single linear regression of within-person variance on the within-class standard deviation at time 1, with fixed effects for question and for person. This amounts to simultaneously testing whether people exhibit more variation in their less constrained beliefs over time than their more-constrained beliefs and whether a belief demonstrates more over-time variation when it is in a less constrained belief system than when it is in a more constrained belief system.

$$\sigma_{ij} = \sigma_{jk} + \mu_i + \mu_j + \epsilon_{ij}$$

The theoretical model ... suggests that people's attitudes . In fact, if the belief system identified at time 1 is a good representation the distribution of beliefs people sample from over time, and if this range of considerations is relatively fixed over time, then the mean value of an attitude within the group at time 1 should predict people's mean responses over time.

$$\mu_{ij} = \mu_{jk} + y_{j,t=1} +$$

5.5 Pattern Prediction

The rest of the hypotheses reflect the claim that the probabilities identified in the latent class analysis reflect the range of considerations that members of that group possess, and that their responses at any time point can be modelled as independent draws from these probabilities. To assess this proposition, I take a predictive approach to comparing the theoretical model outlined above to competing theoretical data-generating processes (???, ???).

Hypotheses 3 and 4 focus on the observed counts of change patterns over time. To illustrate this approach, assume two belief systems that differently constrain people's views on the following question: "Do you think that, in general, a couple without children should end their marriage if it is

empty and unfulfilling, or should they stick with it even if they are not happy?” In one belief system, people are constrained to oppose divorce quite strongly ($Pr(yes) = .9$). These people have many considerations against marriage, but there is a chance that a local event could tip their disposition either way at any particular wave. In the second belief system, people have roughly equal considerations in favor of and opposed to divorce ($Pr(yes) = .5$). They have considerations telling them that people should stay together, and considerations telling them that people should divorce. And which response they give at a particular wave will be affected by the balance of considerations on their mind at any time.

If a person’s response at wave is an independent draw from their consideration set, then people in the first group should say “yes” in both waves about 81 percent of the time ($.9 * .9 = .81$). People in the second group should say “yes” in both waves about 25 percent of the time ($.5 * .5 = .25$). We can calculate the probability of each of the four possible two-wave response patterns, presented below:

Pattern	$Pr(yes) = .9$	$Pr(yes) = .5$
Yes -> Yes	.81	.25
Yes -> No	.09	.25
No -> Yes	.09	.25
No -> No	.01	.25

A key assumption of the belief systems model is that predicting any person’s response at any particular time will be difficult, especially if it is deduced that beliefs are relatively unconstrained in a particular system, such as the rightmost column. But the theoretical model can generate strong predictions of counts of response patterns in the aggregate. We could use the distribution of these two belief systems in the population, as well as the distribution of responses observed at time 1, to generate a range of plausible predictions for the count of each pattern we observe in the data set.

Predicting response patterns in the latent class model requires two steps: sampling class identification and sampling responses. The LCA model assigns each observation a probability of

belonging to each class based on their covariate profile. I sample class assignment from these probabilities. Then, using these class assignments, I sample responses from the probabilities assigned to members of that class. I can then count the number of people who demonstrate each response patterns (“Agree” in wave 1 to “Disagree” in wave 2) and compare that to the observed count of response patterns. While the theoretical framework makes within-class predictions, because people are probabilistically assigned to different classes and to make comparisons to other theoretical processes I aggregate counts of response patterns at the question level, rather than the class level. I sum the squared deviations from the expectation to penalize larger differences between the expected and observed counts.

$$\lambda_i = \sum_{y_{t=1}=i} \sum_{y_{t=2}=k} (Exp - Obs)^2$$

Because both class assignment and response probabilities reflect sources of uncertainty, I iterate this process 10,000 times to generate a distribution of accuracy that reflects the probabilities of class assignment and response probabilities.

This range of numbers provides a quantification of how good the model predicts response patterns over time, with 0 being a perfect prediction, but it is meaningless on its own, since there is no clear alternative expectation for how many counts we observe. It is unlikely that any model would perfectly predict responses over time. However, I can compare whether this theoretical process does a better job predicting the count of observed changes over time than other theoretical models, such as a model that predicts that people give the exact same response in time 2 that they gave at time 1, one that predicts that people sample randomly from the full belief system with equal probability, or one that assumes beliefs are drawn from the sample probabilities observed at time 1 or 2. These are implausible models, but we can outline more theoretically grounded alternatives.

The clearest theoretically grounded alternative explanation would suggest that people have more or less ideosyncratic belief systems (or sets of considerations) as a function of their social experiences. In contrast to the belief systems model, this theory would expect no systematic relationship between beliefs in this framework. Instead, people would receive separate influences on each belief

from their social environments – churches, schools, families, friends, etc. – and these would shape their responses at each wave.

To estimate these ideosyncratic patterns, I conduct a multinomial logistic regression for each individual attitude at time 1 on the range of covariates included in the latent class analysis.⁵ This produces a set of individual-specific probabilities of giving each response to a question. I then use those probabilities to simulate potential responses over time and similarly quantify predictive accuracy.

Model comparisons typically penalize models for complexity, as complexity tends to lead to greater predictive accuracy within a sample. The latent class model, while quite complex, is substantially less complex than estimating separate models for each response. The latent class analysis estimates 348 separate parameters (coefficients predicting class assignment and probabilities of response in each class for 19 questions), while the multinomial logit model requires 952 parameters. If the latent class model makes better predictions, there is no reason to prefer the approach of estimating separate probabilities for each response on the grounds of parsimony. There are obvious ways to simplify both models by removing parameters that do not aid in prediction, or by treating responses as ordinal rather than multinomial. However, the main goal of using the same predictors and same outcome scale is to design two models that reflect two similar but distinct theoretical processes: one where beliefs influence and constrain each other, and one where they do not.

5.6 Changing Circumstances

To this point, hypothesis testing has been oriented toward establishing that latent class analysis as a good methodological fit for the theoretical concept of a belief system and the predictions it makes over time. If that is established, then we can use the deduced belief systems to compare the relative

⁵An common alternative to the assumption that each person's response at each wave is a draw from a multinomial distribution is to assume that each person's response is a latent variable observed with error. This would model the outcome not as a set of independent categories (multinomial logit/probit), but as manifestation of a latent variable (ordinal logit/probit). In practice, the multinomial logit is a less constrained instantiation of the ordinal logit model. If attitudes do reflect an underlying latent construct, the multinomial logit will reflect this structure, but the reverse is not true. Since I am not principally concerned with model parsimony, but rather on adjudicating theoretical processes, I use the multinomial logit model.

influence of the belief system with social structural changes that might produce changes in beliefs over time.

To test the influence of organizational change and social network change, I use the coefficients derived from the latent class and multinomial logit model at time 1 to predict class assignment and responses at time 2 using social structural and social network variables observed at time 2. If changing circumstances – increased church attendance or a more diverse friend group, for example – have the effect of producing changes in attitudes, then using information about social change between waves will produce better estimates of the patterns of change over time.

To ensure comparability across prediction models, each prediction model uses all people with full beliefs at time 1 and all observed covariates at times 1 and 2. A handful of people with covariates at time 2 failed to answer some of the belief questions. They are evaluated on the questions we do observe them on, meaning there is some small variation in the counts of responses tested for each question.

6 Results

The results proceed in three parts. First, I deduce and explain the belief systems identified through latent class analysis. Second, I test the proposition that the constraints implicit in each belief system are good predictors of over-time change. Third, I adjudicate the competing influences of the belief system and social structures in predicting responses over time.

6.1 Belief Systems

Based on goodness of fit measures and substantive interpretability, I selected and present a five-class model to summarize the belief systems across the three domains outlined above. Figure ### presents the expected probability of each response option for all 19 questions for all of the classes. There is a lot of information contained in the figure, but there are some obvious patterns. I briefly summarize each belief system, giving a substantive interpretation based on response probabilities and covariates,

as well as the implications for over-time change that they imply. Appendix A outlines the model selection process.

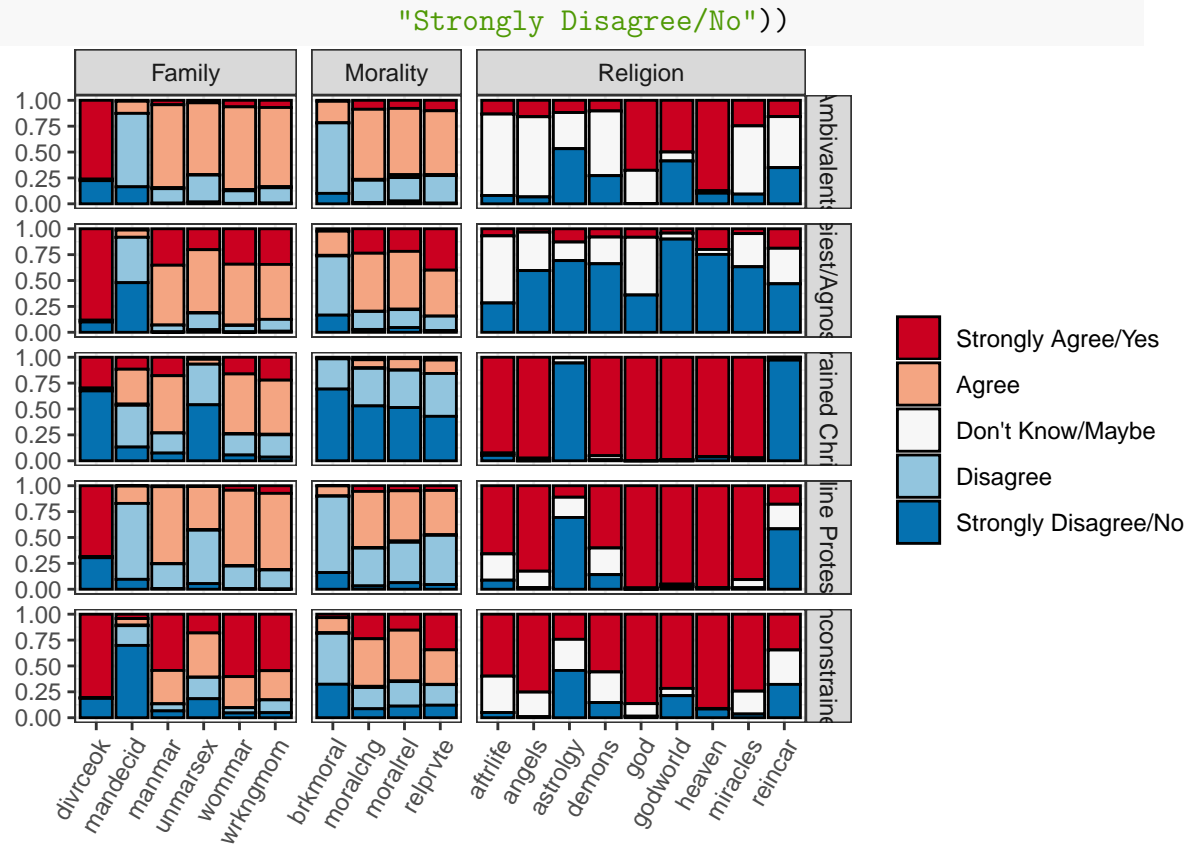
```
load("~/Dropbox/rethinking_constraint/lca5.Rdata")

tidy(15) %>%

  mutate(cat = ifelse(variable %in% c("aftrlife", "angels", "demons", "astrology",
                                     "reincar", "godworld", "heaven", "god",
                                     "miracles"),
                     "Religion",
                     ifelse(variable %in% c("moralrel", "moralchg", "brkmoral",
                                             "relprvte"),
                           "Morality", "Family"))) %>%

  mutate(class = recode(class, "1"="Ambivalents",
                          "2"="Atheiest/Agnostics",
                          "3"="Mainline Protestants",
                          "4"="Constrained Christians",
                          "5"="Unconstrained")) %>%

  ggplot(aes(x = variable, y = estimate, fill = as.factor(outcome))) +
  geom_bar(stat = "identity", position = "stack", color = "black") +
  facet_grid(class~cat, scales = "free_x", space = "free") +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 60, hjust = 1)) +
  labs(x = "", y = "", fill = "") +
  scale_fill_brewer(type = "div", palette = 5,
                   labels = c("Strongly Agree/Yes",
                              "Agree", "Don't Know/Maybe",
                              "Disagree",
```



Constrained Christians: The first group, which comprises about 10 percent of survey respondents, displays the most strongly constrained religious beliefs. Almost everybody in this class expresses a belief in the major tenets of Christian theology, and they uniformly reject non-Christian beliefs (reincarnation and astrology). They strongly contrast with other classes in being much more likely to say they disagree and strongly disagree with moral relativism (moralchg; moralrel) and the notion that religion is a private matter (relprvte). Identification as an Evangelical Christian is a strong predictor of being in this class, as is frequent attendance at religious services.

A key feature of this class is that they are less constrained in their beliefs about family and gender than many of the other classes. This lack of constraint arises because their belief space is broader than that of other classes; their belief system presents them considerations that are at odds with the prevailing culture that views divorce as an acceptable option. Similarly, while most other groups are constrained to the “disagree” side of the scale on whether “Most of the important decisions in the life of the family should be made by the man of the house,” members of this group occasionally

agree or strongly agree. They are also the group most likely to say that sex before marriage is not acceptable.

Under the belief system framework outlined above, we should expect members of this group to be highly unlikely to make changes in their beliefs about religious phenomena, both relative to their other beliefs and relative to other groups. They will also be more less likely to change their views of morality than other groups. At the same time, because they have these conflicting considerations about family structures, they should be more likely to change those beliefs – both more likely to change those than other groups and more likely to change those than other beliefs.

Atheists/Agnostics: The second class, which comprises about 15 percent of respondents, displays a rejection of religious beliefs. They either reject or question the principal components of Christian theology. At the same time, they also reject astrology and reincarnation. In fact, they look more similar to the most constrained religious group on these two issues than other classes do. They are the most constrained to the “relative” side of the moral relativism-moral absolutism scales. In terms of covariates, they tend not to identify as identify with a religious denomination or attend religious services. However, people who identify as Jewish also strongly cluster in this group.

This group is also quite constrained on issues of Christian beliefs, family structure, and morality. I expect them to demonstrate limited change over time in their beliefs about family structures.

Ambivalent: The third group is characterized by a high degree of uncertainty on religious and moral beliefs. They are the most likely to say they don’t know in response to questions about the existence of angels, demons, and god, as well as the non-Christian belief questions such as astrology and reincarnation. These respondents tend to be Catholic or unaffiliated with a religious tradition.

A key prediction for this group is that they ... On issues such as the existence of angels and demons, they will actually , because they feel comfortable, for whatever reason, saying . They have a belief system that facilitates saying ”

Mainline Christians: This group most closely resembles the strong religious group in their responses to questions about religious beliefs, but their constrained religious beliefs do not appear

to spill over into other domains. Members of this group appear torn between their religious commitments and the culture of contemporary American society, or at least have not taken the time to reconcile these contradictions, producing relatively high levels of ambivalence on issues of family structure and morality, rarely giving “strong” responses to either. This is the largest class in the data set, drawing members from all religious groups, principally people who do attend religious services, but do not attend them frequently.

Because they appear to have conflicting considerations on questions of morality – strong Christian religious beliefs and progressive views on family – they have considerations that push them in both directions on morality. As a result, they will likely vacillate around the scale midpoint over time.

Unconstrained: The final group demonstrates little constraint across the board.

While I call these five groups “belief systems,” it is not necessary that members of this group see these domains as connected. It could very well be the case that the group I have deemed mainline protestants do not see connections between family life, morality, and religious behavior. Their thought in these domains be the product of diverse influences – schooling, parent’s education, social networks, and religious participation – that shape the range of considerations they hold. What these belief systems seek to represent are groups of people with similar sets of considerations in their cognition. The central assumption is that people’s responses over time on all 19 issues should resemble independent draws from these distributions.

The assumption of the model outlined here is that people in the strongly religious group do not have an attitude about divorce. They have a set of considerations that leads them to respond to “no” about three-fourths of the time. But any particular person in that group might say “yes” about a quarter of the time, depending on his or her circumstances. The only way to test this proportion is to test whether people appear to behave that way over time. I do that now.

6.2 Over-Time Change

Figure ... plots the average within-question, within-class standard deviation at time 1 against the average within-question, within-person standard deviation over time, group by question and class. If within-group constraint is a good proxy for within-person considerations, there should be a positive correlation between these two measures.

```
load("~/Dropbox/rethinking_constraint/sd_data.Rdata")

library(ggrepel)

sd_data %>%

  ggplot(aes(x = grp_sd, y = mean_sd, fill = as.factor(predclass))) +
  geom_abline(slope = 1, linetype = 2, color = "gray") +
  geom_point(shape = 21) +
  geom_text_repel(aes(label = question), size = 2) +
  labs(x = "Within-Class S.D., wave 2",
       y = "Avg. Within-Person Change between Wave 2 and 3",
       fill = "Class") +
  theme_minimal() +
  scale_fill_brewer(type = "qual")
```


[Table 1 about here.]

As expected, Table ### shows a strong positive association between within-group variance at time 1 and within-person change over time. In other words, consistent with Hypothesis ###, people are more likely to change attitudes that are less constrained in their group at time 1. And consistent with Hypothesis ###, within questions, groups that are less constrained exhibit more change their answers over time.

6.3 Response Patterns

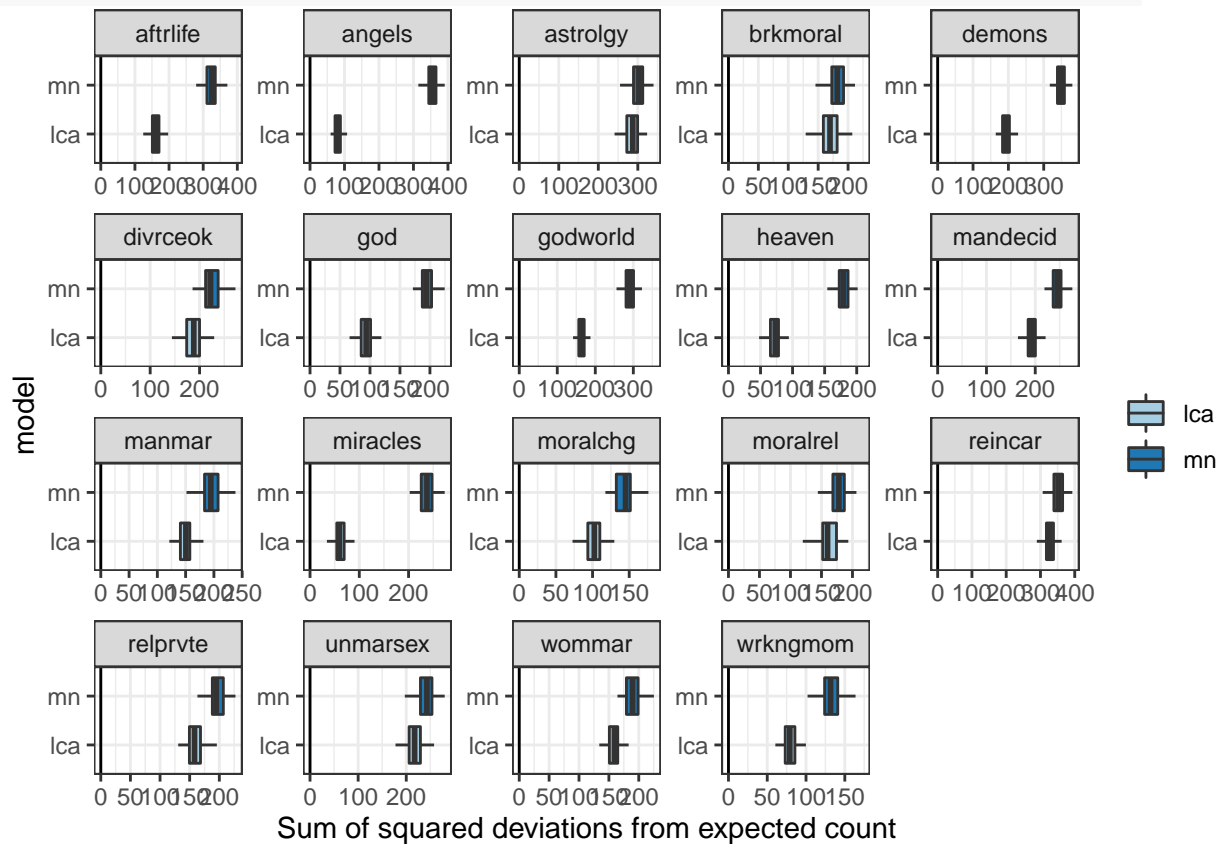
While the regression above presents strong evidence that people are more likely to change their less constrained beliefs and that the same beliefs change less in more constrained belief systems, the belief structure model outlined above makes a stronger prediction: that constraints not only predict how much responses will change, but how often members of each group will give certain responses over time. Figure XXX presents the sum of squared deviations from the expected counts for predictions made using the latent class model to predictions generated using a separate multinomial logit model for each attitude question.

```
load("~/Dropbox/rethinking_constraint/mn_ssd.Rdata")
load("~/Dropbox/rethinking_constraint/lca_ssd.Rdata")

bind_rows(mn_ssd, lca_ssd) %>%
  mutate(sd = sqrt(sum_ssd)) %>%
  ggplot(aes(x = model, y = sd, fill = model)) +
  geom_hline(yintercept = 0) +
  geom_boxplot(outlier.shape = NA) +
  coord_flip() +
  facet_wrap(~question, scales = "free") +
  theme_bw() +
  labs(y = "Sum of squared deviations from expected count", y = "",
```



```
fill = "") +
scale_fill_brewer(type = "qual", palette = "Paired")
```



The predictions generated through the latent class model consistently outperform the predictions made through the multinomial logit model. For some questions, especially the Christian religious beliefs, the differences between the two models is stark. Other questions are less conclusive, but the latent class model still outperforms the ideosyncratic beliefs model on average. These latter beliefs – astrology, reincarnation, and whether sex before marriage is acceptable – tend to be the least different across belief systems, suggesting that the other beliefs in the system exhibit little constraining influence on how people understand them. They also tend to be the hardest to predict in general. The question about premarital sex is distinct in reflecting a high degree of durable change in responses over time.

These results suggest that latent class analysis estimates a set of response probabilities that closely resemble the probabilities that members of those classes have of giving those responses over

time. While these predictions are better for some questions than others, they generate better predictions than a model that suggests beliefs are unconstrained from each other.

These results appear tell us something about the consideration sets that people bring with them to interviews, but it cannot deduce whether these are principally the result of cognitive structuring or social influence. I now turn to adjudicating these competing explanations of attitude patterns.

6.3.1 Changing Social Circumstances

I test hypothesis 4 to adjudicate the competing influences of belief systems and social structures in predicting attitude change over time. If attitude constraints are principally the result of early life socialization, then the belief structure observed at wave 1 should outperform a model that takes changing social circumstances into account. I replicate the approach outlined above, using time 2 covariates to predict changes in response patterns between time 1 and time 2. Figure ... compares the prediction from the belief system observed at time 1 to predictions generated through a multinomial and latent class model using covariates observed at time 2.

The time 1 belief system outperforms both an ideosyncratic influence model (the multinomial model) that uses time 2 covariates and a model that uses covariates at time 2 to predict new membership in belief systems. There is little change in the predictions for the multinomial logit model compared to just using wave 1 covariates, but the latent class model performs worse when we account for changes in social structure.

This appears to be principally because people decrease their religious participation and increase between times 1 and 2, which should have the effect of shifting people to new belief systems. This change in covariates is not surprising, as the gap between these waves principally reflects people leaving their parent's home and relatively homogenous communities and transitioning to independent life, college, and the workforce, but it is surprising that these changes produce worse predictions of what people believe.

7 Discussion

This paper had two related goals. First, it sought to rethink how researchers interested in the measurement of culturally structured cognition conceptualize and measure belief systems in the general public. I argued that because the schematic structuring of cognition happens below the level of a survey response, measuring the pairwise relationship between these responses can produce misleading conclusions about how culturally shaped cognition works in people's heads. Similarly, I argued that existing measures of schematic cognition do not fully take into account how culturally shared schematic cognition might produce variation in responses over time that reflect those structures. As an alternative measure, I argued that latent class analysis could be used to deduce belief systems that manifest as shared probabilities of giving certain responses to different questions over time.

Using Latent Class Analysis, I deduced five belief systems in the population of adolescents surveyed in the NSYR regarding family structure, moral, and religious beliefs. These systems differ strongly in the constraints they placed on people's cognition. The first three hypothesis tests provide a broad test of whether the constraints observed at time 1 predicted people's change over time, finding that the within-group constraints implied by the model at time 1 are reflected in individuals' change over time. The key finding of this paper is that the probabilities derived across people at a single point in time provide a remarkably good prediction of how people changed over time.

As a second goal, the paper sought to adjudicate the relative influence of such cultural-cognitive structures on opinion behavior over time compared to social-structural influences such as social networks and organizational participation. Results from the fourth hypothesis test suggest that the constraints (or lack of constraints) present at time 1 better predict the aggregate pattern of responses over time than models that account for changing social circumstances.

These findings suggest that research focusing on explaining attitude behavior over time might put too much emphasis on the social structures at the expense of cognitive structures formed early in life.

To be clear, these results should not downplay the role of organizational structures and social networks in shaping people's belief patterns. Organizational participation, especially religious

tradition and frequency of religious service attendance, were strong predictors of belief systems at wave 1.

7.1 Implications for Cultural Sociology

The results also reinforce the finding that many attitudes appear to . Across many of the questions explored above, people appear to internalize competing This paper suggests that ... because the ...

7.2 Methodological Implications

Measuring culture is challenging, and measuring culture in the morass that is people's cognition is even moreso. ... look for the signature of shared culture in stability. But shared culture is often heterogeneous and conflicting, producing instability. But that does not make this any less "culture." A key argument of this paper is that the result of shared cultural structures is instability.

The results should also pose a challenge to how we understand measurement error. The central assumption of measurement error arguments for the inconsistency of beliefs is that inconsistency is inherent in questions. What the latent class analysis shows is that inconsistency is a relationship between people's cognition and the question they answer.

7.3

8 Conclusion

deducing belief systems. The attitudes studied here are , and strongly related in some belief systems.

An implication of this model is that more constrained beliefs should be more predictive of behavior than less constrained belief. Because Constrained Christians have a clear view of the existence of god that seems relatively impervious to temporary influences on the consideration set, they can bring this consideration ... Previous work shows that people who live in environments that contain heterogeneous cultural models show a weaker link between their own expressed beliefs at a

single survey wave and their behavior over time (Harding 2007).

An important caveat to the above presentation is that Wave 2 of the NSYR – time 1 in this study – occurs at what seems to be a particularly formative period in people’s life course. Respondents were between the ages of 16 and 20 when they were interviewed for wave 2 of the NSYR. Existing research suggests that people’s attitudes on a range of issues appear to crystalize prior to adulthood (Kiley and Vaisey 2020; ???; Vaisey and Miles 2017). It is highly likely that ... always be the case that the first wave of a panel survey is as strongly predictive for each belief system. For example, it is not clear if using wave 1 of the NSYR, when respondents were between the ages ...

There are two general reasons why we should expect constrained beliefs to demonstrate greater stability. First, people with constrained beliefs will demonstrate less change in their social contexts. Strong belief systems guide people’s behavior across domains, including the networks people select into, the institutions in which they choose to participate, and more (Vaisey and Lizardo 2016).

9 References

- Ansolabehere, Stephen, Jonathan Rodden, and James M. Snyder. 2008. "The Strength of Issues: Using Multiple Measures to Gauge Preference Stability, Ideological Constraint, and Issue Voting." *American Political Science Review* 102 (2): 215–32. <https://doi.org/10.1017/S0003055408080210>.
- Baldassarri, Delia, and Andrew Gelman. 2008. "Partisans Without Constraint: Political Polarization and Trends in American Public Opinion." *American Journal of Sociology* 114 (2): 408–46.
- Baldassarri, Delia, and Amir Goldberg. 2014. "Neither Ideologues nor Agnostics: Alternative Voters' Belief System in an Age of Partisan Politics." *American Journal of Sociology* 120 (1). The University of Chicago Press: 45–95. <https://doi.org/10.1086/676042>.
- Bonikowski, Bart, and Paul DiMaggio. 2016. "Varieties of American Popular Nationalism." *American Sociological Review* 81 (5). SAGE Publications Inc: 949–80. <https://doi.org/10.1177/0003122416663683>.
- Boutyline, Andrei. 2017. "Improving the Measurement of Shared Cultural Schemas with Correlational Class Analysis: Theory and Method." *Sociological Science* 4 (May): 353–93. <https://doi.org/10.15195/v4.a15>.
- Boutyline, Andrei, and Stephen Vaisey. 2017. "Belief Network Analysis: A Relational Approach to Understanding the Structure of Attitudes." *American Journal of Sociology* 122 (5). The University of Chicago Press: 1371–1447. <https://doi.org/10.1086/691274>.
- Converse, Philip E. 1964. "The Nature of Belief Systems in Mass Publics (1964)." In *Ideology and Discontent*, edited by D. E. Apter, 18:206–61. New York: Free Press. <http://www.tandfonline.com/doi/abs/10.1080/08913810608443650>.
- DellaPosta, Daniel. 2020. "Pluralistic Collapse: The 'Oil Spill' Model of Mass Opinion Polarization." *American Sociological Review* 85 (3). SAGE Publications Inc: 507–36. <https://doi.org/10.1177/0003122420922989>.
- DellaPosta, Daniel, Yongren Shi, and Michael Macy. 2015. "Why Do Liberals Drink Lattes?" *American Journal of Sociology* 120 (5). The University of Chicago Press: 1473–1511. <https://doi.org/10.1086/681254>.
- DiMaggio, Paul. 1997. "Culture and Cognition." *Annual Review of Sociology* 23: 263–87.
- DiMaggio, Paul, Ramina Sotoudeh, Amir Goldberg, and Hana Shepherd. 2018. "Culture Out of Attitudes: Relationality, Population Heterogeneity and Attitudes Toward Science and Religion in the U.S." *Poetics* 68 (June): 31–51. <https://doi.org/10.1016/j.poetic.2017.11.001>.
- Freeder, Sean, Gabriel S. Lenz, and Shad Turney. 2019. "The Importance of Knowing 'What Goes with What': Reinterpreting the Evidence on Policy Attitude Stability." *The Journal of Politics* 81 (1): 274–90. <https://doi.org/10.1086/700005>.
- Goldberg, Amir. 2011. "Mapping Shared Understandings Using Relational Class Analysis: The Case of the Cultural Omnivore Reexamined." *American Journal of Sociology* 116 (5). The University of Chicago Press: 1397–1436. <https://doi.org/10.1086/657976>.
- Goldberg, Amir, and Sarah K. Stein. 2018. "Beyond Social Contagion: Associative Diffusion and the Emergence of Cultural Variation." *American Sociological Review* 83 (5). SAGE Publications Inc: 897–932. <https://doi.org/10.1177/0003122418797576>.
- Harding, David J. 2007. "Cultural Context, Sexual Behavior, and Romantic Relationships in Disadvantaged Neighborhoods." *American Sociological Review* 72 (3): 341–64. <https://doi.org/10.1177/000312240707200302>.

- Hill, Jennifer L., and Hanspeter Kriesi. 2001. "An Extension and Test of Converse's "Black-and-White" Model of Response Stability." *The American Political Science Review* 95 (2). [American Political Science Association, Cambridge University Press]: 397–413.
- Hunzaker, M. B. Fallin. 2016. "Cultural Sentiments and Schema-Consistency Bias in Information Transmission." *American Sociological Review* 81 (6): 1223–50. <https://doi.org/10.1177/0003122416671742>.
- Hunzaker, M.B. Fallin, and Lauren Valentino. 2019. "Mapping Cultural Schemas: From Theory to Method." *American Sociological Review* 84 (5). SAGE Publications Inc: 950–81. <https://doi.org/10.1177/0003122419875638>.
- Kiley, Kevin, and Stephen Vaisey. 2020. "Measuring Stability and Change in Personal Culture Using Panel Data." *American Sociological Review* 85 (3). SAGE Publications Inc: 477–506. <https://doi.org/10.1177/0003122420921538>.
- Lewis, Kevin, and Jason Kaufman. 2018. "The Conversion of Cultural Tastes into Social Network Ties." *American Journal of Sociology* 123 (6): 1684–1742. <https://doi.org/10.1086/697525>.
- Lizardo, Omar. 2006. "How Cultural Tastes Shape Personal Networks." *American Sociological Review* 71 (5): 778–807. <https://doi.org/10.1177/000312240607100504>.
- Lizardo, Omar, and Michael Strand. 2010. "Skills, Toolkits, Contexts and Institutions: Clarifying the Relationship Between Different Approaches to Cognition in Cultural Sociology." *Poetics* 38 (2): 205–28. <https://doi.org/10.1016/j.poetic.2009.11.003>.
- Martin, Jack K., Bernice A. Pescosolido, and Steven A. Tuch. 2000. "Of Fear and Loathing: The Role of 'Disturbing Behavior,' Labels, and Causal Attributions in Shaping Public Attitudes Toward People with Mental Illness." *Journal of Health and Social Behavior* 41 (2): 208. <https://doi.org/10.2307/2676306>.
- Martin, John Levi. 2000. "The Relation of Aggregate Statistics on Beliefs to Culture and Cognition." *Poetics* 28 (1): 5–20. [https://doi.org/10.1016/S0304-422X\(00\)00010-3](https://doi.org/10.1016/S0304-422X(00)00010-3).
- . 2002. "Power, Authority, and the Constraint of Belief Systems." *American Journal of Sociology* 107 (4): 861–904. <https://doi.org/10.1086/343192>.
- . 2010. "Life's a Beach but You're an Ant, and Other Unwelcome News for the Sociology of Culture." *Poetics* 38 (2): 229–44. <https://doi.org/10.1016/j.poetic.2009.11.004>.
- Miles, Andrew. 2015. "The (Re)Genesis of Values: Examining the Importance of Values for Action." *American Sociological Review* 80 (4): 680–704. <https://doi.org/10.1177/0003122415591800>.
- Rawlings, Craig M. 2020. "Cognitive Authority and the Constraint of Attitude Change in Groups." *American Sociological Review* 85 (6). SAGE Publications Inc: 992–1021. <https://doi.org/10.1177/0003122420967305>.
- Rawlings, Craig M., and Clayton Childress. 2019. "Emergent Meanings: Reconciling Dispositional and Situational Accounts of Meaning-Making from Cultural Objects." *American Journal of Sociology* 124 (6): 1763–1809. <https://doi.org/10.1086/703203>.
- Swidler, Ann. 1986. "Culture in Action: Symbols and Strategies." *American Sociological Review* 51 (2): 273. <https://doi.org/10.2307/2095521>.
- . 2001. *Talk of Love: How Culture Matters*. Chicago: University of Chicago Press.
- Vaisey, S., and O. Lizardo. 2010. "Can Cultural Worldviews Influence Network Composition?" *Social Forces* 88 (4): 1595–1618. <https://doi.org/10.1353/sof.2010.0009>.
- Vaisey, Stephen. 2009. "Motivation and Justification: A Dual-Process Model of Culture in Action." *American Journal of Sociology* 114 (6): 1675–1715. <https://doi.org/10.1086/597179>.
- . 2014. "The 'Attitudinal Fallacy' Is a Fallacy: Why We Need Many Methods to Study Culture."

- Sociological Methods & Research* 43 (2): 227–31. <https://doi.org/10.1177/0049124114523395>.
- Vaisey, Stephen, and Omar Lizardo. 2016. “Cultural Fragmentation or Acquired Dispositions? A New Approach to Accounting for Patterns of Cultural Change.” *Socius* 2 (January). SAGE Publications: 2378023116669726. <https://doi.org/10.1177/2378023116669726>.
- Vaisey, Stephen, and Andrew Miles. 2017. “What You Can—and Can’t—Do with Three-Wave Panel Data.” *Sociological Methods & Research* 46 (1). SAGE Publications Inc: 44–67. <https://doi.org/10.1177/0049124114547769>.
- Zaller, John. 1992. *The Nature and Origins of Mass Opinion*. Cambridge Studies in Public Opinion and Political Psychology. Cambridge: Cambridge University Press. <https://doi.org/10.1017/CBO9780511818691>.

	Model 1
grp_sd	0.44*** (0.01)
R ²	0.05
Adj. R ²	−0.01
Num. obs.	44577

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 2: Statistical models