Chapter 4: Moral Representation

Brad Jones
18 August 2015

Up to this point, I have been primarily concerned with how individuals apply general moral values to specific political attitudes. In Chapter 1, I argued that moral values precede rational considerations and are the raw materials from which (many) political attitudes are built. After an extended methodological diversion in Chapter 2 discussing the measurement of these moral values, Chapter 3 showed that measures of individuals’ moral foundations can do a great deal of work in explaining variation in political attitudes. This is obvious when we look at the moral divide between partisans of each of the major political parties, but moral diversity within each of the major parties can explain the sometimes uncomfortable alliances that exist between people who are nominally “on the same side.” In short, the dissertation to this point has offered compelling evidence that individual political attitudes are a reflection of more deeply held moral predispositions.

In this chapter, I change my focus from the individual level to the aggregate level. If it is true that general moral principles account for differences between individuals as I showed in Chapter 3, it should also be the case that these differences add up to aggregate effects. Do aggregates of individuals with their own unique moral priorities exert measurable influence on their political representatives? The larger story that I am trying to tell in this project is that specific political attitudes are built upon intuitions about “rightness” and “wrongness” that constitute fundamental disagreements. Political elites have incentives to mobilize these basic concerns in the ways in which they frame political issues (as I will discuss more in the next chapter), and these attempts to structure politics around intuitive moral divides should show up in elite behavior like position taking.

I will take up the question of how basic moral values affect public policy by looking at how variation in moral priorities across congressional districts affects congressional behavior. To do so, I will first need to construct measures of the moral foundations at the congressional district level. I employ a model based strategy to generate small area estimates. This approach is similar to that proposed by Lax and Phillips (2009), but the
nature of the data I am using necessitate some adaptations to the method. My measures of congressional district moral foundations are built from a large \((n > 150,000)\) database of responses to the Moral Foundations Questionnaire (MFQ). The MFQ is long enough\(^1\) that it is rarely included in nationally representative surveys. The database that I rely upon makes no claims of representativeness, but my model attempts to account for the selection bias in the data and produce adjusted measures that are reflective of the general population.

After demonstrating the face validity of my measures of the moral foundations at the congressional district level, I discuss some the challenges associated with finding real effects amidst a vast number of roll-call votes cast. It would be easy enough to find seemingly “statistically significant” effects with purely random measures given the vast number of roll-call votes that are cast during every legislative session, so I employ a non-parametric test to separate out the signal from the noise. I find that, even after controlling for district partisanship (a factor which explains over two thirds of the variance in the roll-call votes I consider here), the moral foundations are robust and significant factors in a substantial number of cases. The roll-call voting behavior of members of Congress regularly shows responsiveness to the moral considerations of their constituents.

**Moral Representation**

Recently, political scientists have devoted a lot of attention to the ways in which political polarization potentially distorts representation. For example, Bafumi and Herron (2010) scale constituents and legislators into the same ideological space and show a substantial gap between representatives from both parties and almost every person in the mass public. When party control shifts in a district, the hapless citizenry is “leapfrogged” by increasingly extreme legislators. In a polarized political climate, it would seem that there is little hope for the average citizen to have her interests represented in congress.

The story is perhaps not so bleak as painted by Bafumi and Herron. After all, one notable difference between average citizens and the legislators who represent them is that the latter are embedded within institutions designed to shape their behavior along a partisan dimension (Cox and McCubbins, 2005). The average citizen is not nearly so constrained in her opinions about specific issues (Converse, 2006). Indeed, as I argue

---

\(^1\)I actually combine responses from 3 different versions of the MFQ. A “short” 20-item measure, the standard 30-item measure as described by citegraham2011mapping that contains the 20-item measure, and a longer 48-item measure that contains the 30-item measure and adds a few more items. See Chapter 2 for more details about the use of these different scales.
in Chapter 2, individual preferences on political issues are shaped in large part by their moral intuitions,\(^2\) and these multidimensional predispositions cannot be cleanly divided into two camps. In a legislature however, one of the primary roles of the institution is to reduce the dimensionality of conflict thus making constructive legislative action possible (Shepsle and Weingast, 1981; Aldrich, 2011; Jones, Talbert and Potoski, 2003).

My contention in this chapter is that there is something more going on than just a left-right divide in congressional voting. Despite (or perhaps because of) the overwhelming pressure of the institution to structure conflict along a small number of dimensions, election-minded politicians will seek out opportunities to represent their constituents’ moral concerns that are not so neatly structured. They are constrained in significant ways by the congressional agenda, but if they are acting in accordance with their constituents’ moral concerns, we ought to be able to detect systematic deviations from the predominant unidimensional pattern that we see in almost all votes.

In this chapter, I am arguing that political elites, in order to succeed in reelection, must become intuitive moral psychologists. Politicians should be selected for their ability to capitalize on the underlying value structure in the electorate, and the system should come to be oriented around these enduring values. Under this view, the structure of individual-level values operates as a significant constraint on elite behavior. At the elite strategy level, we should observe elites operating under constraints placed upon them by the moral concerns of their district. Elite appeals and position-taking behavior should be targeted at the particular concerns of the average voter in their districts.

Given the overwhelming explanatory power of one (or maybe two) dimensions in explaining legislative decision making in the United States (Poole, 2005), it is perhaps surprising that there should be room for anything else in models of elite vote choice. In the contemporary Congress, rates of party-line voting are extremely high and the ideological distance between the two parties is wide and enduring. My measures of the moral foundations of each congressional district can only be plausibly extended back in time to around 2007. During this period, a simple bivariate probit model with district partisanship\(^3\) correctly predicts 90% of the voting decisions in an average roll-call vote.\(^4\) In almost

---

\(^2\) Although, the most engaged segment of the populace does seem to let partisanship trump moral intuitions at least some of the time.

\(^3\) In this chapter, when I refer to “district partisanship,” I am referring to the two-party vote for president in a member’s district in the presidential election preceding the vote. For example, when the dependent variable is a vote that occurred in 2009, the district partisanship variable is defined as the proportion of the vote that went to Obama in the 2008 election excluding minor party candidates.

\(^4\) At several points in this chapter, I will refer to the proportion of votes that were “correctly predicted.” For my purposes, correctly predicted refers to cases where the predicted probability of voting “yea” was greater than 0.5 and the legislator actually voted “yea,” or conversely the predicted probability of voting
15 percent of the votes (925), district partisanship cleanly separates the “yea” votes from the “nays” with no errors.

In the subset of votes that I examine in this chapter,\(^5\) accounting only for the partisan complexion of a legislator’s district (as measured by the two-party presidential vote in his or her district) explains more than two-thirds of the variation on average. For some votes, the explanatory power of district partisanship exceeds 80%. The contemporary U.S. Congress presents a difficult case for discovering any additional factors in roll-call voting.

Our understanding of legislative institutions suggests when these moral factors might be relevant. Legislators who find themselves in the majority party should be more constrained along the single dominant dimension. Legislators in the minority are relatively more free to act in accordance with their constituents’ demands. Fortunately (at least for the purposes of understanding the process), party control switched hands dramatically during the period of my study. The cases I examine span the 110th through 113th congresses. During the 110th and 111th congress, Democrats held majority control of the House. The 2010 election saw a dramatic reversal in fortunes for the Democratic party, and the 112th and 113th congresses had Republican majorities. This variation in party control allows a deeper look into the factors that contribute to legislative decision making.

Moral Foundations Theory

In this chapter and elsewhere,\(^6\) I operationalize the moral priorities of individuals by their scores on the Moral Foundations Questionnaire. Moral Foundations Theory describes a small set of universal moral concerns that are found to varying degrees in all people. The theory was proposed by Jonathan Haidt (2001) and others (Haidt and Graham, 2007; Graham, Haidt and Nosek, 2009; Haidt, 2012; Koleva et al., 2012). Haidt’s conceptualization of moral values builds from cross-cultural psychology, anthropology, philosophy, and even primatology. He and his colleagues describe a set of moral intuitions that are common to all humans. The most recent iteration of the theory asserts that five founda-

\(^5\)“yea” was less than 0.5 and the legislator actually voted “nay.”

\(^6\)For reasons that I will detail below, I am looking only at intraparty variation in votes where there was substantial division within the party.

\(^6\)This section of the chapter was adapted from a longer introduction in Chapter 1 to introduce the reader to Moral Foundations Theory if this is the only chapter that is read. Careful readers of Chapter 1 and the present section will note many similarities.
tions\(^7\) (Care/Harm, Fairness/Reciprocity, Loyalty/Betrayal, Respect/Subversion, Sanctity/Degradation) can account for a great deal of the commonalities and the variance that we observe between and within cultures across the world. Haidt, Graham, and Joseph (2009) use the metaphor of an equalizer as is found on a home stereo system; individuals have different settings on the equalizer that are partially determined by biological factors and partially culturally determined. Individual differences across the moral foundations account for differential moral judgments. In Western cultures, they have found that political liberals tend to emphasize the Care/Harm and Fairness/Reciprocity foundations while political conservatives seem to place relatively more weight on all five foundations (2009, 113). In practice, this means liberals and conservatives often find it difficult to understand one another, as they are speaking different moral languages. The foundations are listed, along with brief descriptions and associated concepts from the political science literature in Table 1.

\(^7\)Haidt’s most recent work (2012) proposes a sixth foundation, “Liberty/Oppression.” However in most of the data that I have access to, I only have reliable measures of the five foundations most frequently associated with Moral Foundations Theory in the literature. Well-tested measures of this sixth foundation do not yet exist, and I remain somewhat skeptical that it qualifies as a moral foundation in its present incarnation.
<table>
<thead>
<tr>
<th>Domain</th>
<th>Description</th>
<th>Similar concepts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Care / Harm</td>
<td>Related to our long evolution as mammals with attachment systems and an ability to feel (and dislike) the pain of others. It underlies virtues of kindness, gentleness, and nurturance.</td>
<td>“Nurturant Parent Morality” (Lakoff, 2010; Barker and Tinnick, 2006); Post-materialism (Inglehart, 1997)</td>
</tr>
<tr>
<td>Fairness / Cheating</td>
<td>Related to the evolutionary process of reciprocal altruism. This foundation generates ideas of justice, rights, and autonomy.</td>
<td>“Equality of Opportunity” (Feldman, 1988; Jacoby, 2006), fairness (Hochschild, 1986)</td>
</tr>
<tr>
<td>Respect / Subversion</td>
<td>Shaped by our long primate history of hierarchical social interactions. This foundation underlines virtues of leadership and followership, including deference to legitimate authority and respect for traditions.</td>
<td>“Strict Father Morality” (Lakoff, 2010; Barker and Tinnick, 2006), Authoritarianism (Feldman and Stenner, 1997; Stenner, 2005)</td>
</tr>
<tr>
<td>Loyalty / Betrayal</td>
<td>Related to our long history as tribal creatures able to form shifting coalitions. This foundation underlies virtues of patriotism and self-sacrifice for the group. It is active anytime that people feel that it’s “one for all, and all for one.”</td>
<td>Minimal group theory (Tajfel and Turner, 1979), Nationalism (Roccas, Schwartz and Amit, 2010; Li and Brewer, 2004)</td>
</tr>
<tr>
<td>Sanctity / Degradation</td>
<td>Shaped by the psychology of disgust and contamination. This foundation underlies religious notions of striving to live an elevated, less carnal, more noble way. It underlies the widespread idea that the body is a temple which can be desecrated by immoral activities and contaminants (an idea not unique to religious traditions).</td>
<td>Disgust (Inbar, Pizarro and Bloom, 2009; Terrizzi Jr, Shook and Ventis, 2010; Inbar et al., 2012)</td>
</tr>
</tbody>
</table>

Table 1: Descriptions of each moral foundation and some associated concepts. The descriptions were taken from www.moralfoundations.org.
Measurement

My empirical study of the ways in which constituent moral values influence congressional behavior requires measures of constituent moral concern at the congressional district level. In constructing these small-area estimates of the moral foundations, I draw on a large database of responses to the Moral Foundations Questionnaire collected by Ravi Iyer, Jonathan Haidt, and their colleagues at the website www.yourmorals.org (hereafter “YourMorals” data). The data in this paper were collected between June 2007 and May 2013. After filling out some limited demographic and geographic information, individuals filled out the moral foundations questionnaire and had the option of completing other studies at the website. Respondents who filled out the moral foundations questionnaire were self-selected and many came to the website after reading a newspaper editorial or blog post mentioning the research.\(^8\) The database includes responses from more than 150,000 people. Although the data do not constitute representative sample of the population, people from all across the country and of every political persuasion can be found in the database.

The self-selection biases in the YourMorals data mean that it would be unwise to simply disaggregate the data by congressional district to generate the needed measures. Any model-based procedure that did not account for the unrepresentativeness of the sample would be inappropriate. In this paper, I extend one model-based small-area estimation technique for use with unrepresentative samples. Multilevel Regression with Poststratification is one way to generate small area estimates of public opinion (Lax and Phillips, 2009). This method involves dividing the sample into demographically homogeneous cells that can be matched to validated data on the population of interest (usually Census data). A model is fit to the sample data, and the predictions from the model are then projected onto the population figures. It is then a simple matter to generate the estimates of interest by using the predictions from the model applied to the population data.\(^9\)

This approach has been shown to work well when the aim is to smooth out the small-n cells by pulling them toward a group-level mean (e.g. Bayesian shrinkage).\(^10\) However, my problem is slightly different. Lax and Phillips (2009) develop their method with the aim of extrapolating the results of a nationally representative survey to develop state-

---

8The most common referring website was an editorial by Nicholas Kristof which ran in the *New York Times* in May of 2007. The editorial was provocatively titled, “Would you slap your father? If so you’re a liberal.” The piece reported on some of Haidt’s research on the correlations between the moral foundations and political ideology.

9This is an approach that shares many similarities with that taken by Wang et al. (2014).

10Although, Buttice and Highton (2013) raise some important concerns about the use of MRP in cases where the sample size for the original opinion poll is relatively small.
level estimates. I am not so concerned with small sample sizes as I am with the unrepresentativeness of the original sample. There are significant demographic biases in the YourMorals data (e.g. respondents are younger, more educated, less racially diverse), and the self-selected nature of the sample leads me to believe that it will not be sufficient to stratify only on variables that can be found in the Census.

MRP relies upon the idea that, conditional on observable factors, we can estimate some parameter of interest about each of the cells in the model. Another way of stating the problem that faces those who use unrepresentative data is that there is an unobserved factor (selection into the survey) that we cannot condition on. By adding more stratification variables to the model, we might mitigate concerns about representativeness (e.g. the set of stratification variables is more likely to account for variance in the unobserved selection variable). In order to do this, we have to move beyond the narrow set of demographic controls for which we have good population estimates in the Census.

For the purposes of my study, I stratify additionally on partisanship and ideology. The YourMorals database that I am relying upon has severe ideological biases. More than two-thirds of the individuals who filled out the Moral Foundations Questionnaire self-identify as “liberal.” This compares to about 20 percent of people in the general population. Conditioning on ideology and partisanship corrects for one of the most egregious differences between the self-selected respondents and the general population. The details of the estimation procedure are outlined in the appendix at the end of this chapter. For now, I focus on the substantive results generated by the model.

The resulting measures are displayed in Figure 1. The lower panels show the bivariate relationships, and the upper panels show the correlations. There are modest correlations between the moral foundations measures and the presidential vote variable (the highest is between the Respect foundation at -0.3), and the correlations between the different foundations are modest as well. In general, the bivariate relationships between the moral foundations and the presidential vote are as we might expect from findings at the individual level (see Chapter 3). The correlations between the Care and Fairness foundations are positive (districts that place relatively more emphasis on these foundations were more supportive of Obama), and the Loyalty, Respect, and Sanctity foundations all had negative correlations.

Case Selection

In selecting cases for analysis, my decision was guided by two overarching considerations. Firstly, I selected votes that substantially split one or both of the major parties.
Figure 1: Scatterplot Matrix showing the relationships between the moral foundations and Obama’s vote share in the 2008 election. This figure shows the measures from the pre-2011 districts, but the plot would look very similar with the post-2011 districts. The scale for the Obama vote totals is percentage of the vote. The moral foundations measures are on a standardized scale and can be interpreted as the number of standard deviations from the mean of all congressional districts.
Formally, I considered only roll call votes that received between 25 and 75 percent of a party’s support. This was done in part to exclude votes that cleanly divided the parties (with all or almost all of one party in support and all or almost all of the other in opposition). Votes that break along partisan lines are overdetermined in some sense. For the purposes of this chapter, I will consider only variation within each major party.

This is not to say that variation in roll-call voting behavior between the two major parties is not structured in some way by the moral concerns of constituents. Indeed, many of the issues that divide along party lines are justified in moral language (see Chapter 2 for individual level results on point and Chapter 5 for evidence on how the parties frame issues in moral terms), but it is difficult to convincingly separate partisanship and any constituent pressure empirically. Especially in a time of such deep polarization, inter-party competition swamps almost all other effects. Considering each party separately allows more space for uncovering other factors in the voting decision. Although, as I mentioned earlier, even in this subset of cases nearly 70 percent of the variation in roll-call voting within the parties is accounted for by district partisanship.

**Empirical Expectations**

In examining such a broad cross-section of votes, I do not formulate specific expectations concerning the set of moral foundations that should matter in each particular case. It would be possible to cherry-pick a handful of illustrative cases that confirm the hypothesis that constituent morality constrains elite behavior, but it would also be possible to find cases that contradict it. There are too many factors at play in any particular roll-call vote to satisfactorily model them all. For my purposes, I am most interested in how much explanatory power is added by the moral foundations measures to a simple baseline model. In the analyses that follow, I will focus only on variation within the two major parties, and all models will include controls for district partisanship (as measured by presidential election returns). This sets up a very conservative test, as the lion’s share of the variation in congressional behavior falls along one dimension. For the 1276 votes that satisfy my selection criteria, the baseline model correctly predicts (yields a predicted probability of greater than 0.5 for “yea” votes and less than 0.5 for “nay” votes) more than two-thirds of the votes on average. In one case, this figure reaches as high as 87% and in almost every case it is over 50%. Knowing the partisanship of a district explains a good deal of congressional behavior even within each party caucus.

\footnote{11As Aldrich, Montgomery and Sparks (2014) have shown, looking within each party reveals greater ideological diversity than is apparent when considering the parties together.}
My main task in the remaining part of this chapter will be to demonstrate that the moral foundations have something to contribute over and beyond what is explained by district partisanship. I will be specifically examining how including the moral foundations measures in models of roll call voting add to our ability to explain legislative voting behavior in addition to the dominant single dimension of conflict in the modern House of Representatives.

After establishing that there is a “there” there, I will turn to the question of when the moral foundations matter for congressional voting. My expectations here are that the moral foundations will be most likely to matter in cases where party pressure is expected to be low and representatives are more free to vote their (constituency’s) conscience. When a party is in the majority, their party has almost complete control over the agenda (Cox and McCubbins, 2005), and I expect that majority party members will be under pressure to support their party’s agenda at the expense of their (or their constituents’) moral concerns when the vote might be close (e.g. out party support is low). Using a similar logic, when a party is in the minority, they will be under the most pressure to vote a particular way when their votes will not matter towards the passage of the legislation (e.g. it already has a great deal of support from their own party, or it has little support from both parties). By examining the dynamics of partisan support for each bill, we can test these expectations about partisan pressure.

**Results**

As I am interested in how constituent moral values affect elite congressional behavior over and beyond the role of partisanship, I use a simple baseline model to compare the results against. District partisanship can be roughly approximated by looking at the presidential race broken out by congressional district. The share of the two party vote that goes to the Democratic candidate correlates strongly with other measures of congressional ideology such as NOMINATE scores or interest group ratings. District partisanship has the advantage of not being constructed from roll-call votes. However, its inclusion also sets up a conservative test for my hypotheses. In Chapter 2, I showed how the moral foundations are related to presidential vote at the individual level, so including presidential vote shares in the model will most likely understate the effect of the aggregate moral foundations measures. I have selected all votes that meet these criteria from the 110th to 113th congresses.\(^{12}\)

\(^{12}\)This approximately matches the time during which the YourMorals data were collected. The vote data was downloaded from http://voteview.com.
To test my claims about the role of the moral foundations in affecting elite behavior, I compare the performance of a very simple baseline model (district partisanship) to the model that includes the moral foundations measures as well as district partisanship. For each vote that split one or both of the major parties (e.g. more than 25% and less than 75% of Democrats voted in favor of a particular bill), I fit two probit models. One with only district partisanship, and one with district partisanship and the aggregate moral foundations measures. It is then a simple matter to calculate the proportional reduction in error (PRE) of the moral foundations model compared against the baseline model.\(^\text{13}\)

The specter of multiple comparisons looms large over this project. Indeed, with more than 1200 votes under consideration, false positives are a virtual certainty. In an effort to address these problems, I adopt a permutation strategy to serve as the baseline for statistical significance rather than the standard approach of comparing p-values to some threshold. Permutation is a well-studied computational technique for addressing many of the problems that can attain when we violate some of the assumptions of classical statistical theory (Gibbons and Chakraborti, 2011).\(^\text{14}\)

**Example Cases**

**Republican Support for the Federal Employees Paid Leave Act**

The Federal Employees Paid Parental Leave Act of 2008 proposed to provide two months of paid leave to federal employees who qualify. This act had the overwhelming support of Democrats (only one Democrat voted against the bill). It drew only tepid support from fifty Republicans (just over 25% of the caucus). In a statement made after the bill’s passage, the lone Republican co-sponsor Tom Davis (VA-11) said “This measure, which I’ve pushed for years, says to employees, ‘We care about you and your family. We want you to stay with us.’ But it’s more than a recruitment and retention tool. It’s a matter

\(^{13}\)PRE is simply the difference between the proportion of cases that were correctly predicted under the moral foundations model and the proportion of cases that were correctly predicted under the baseline model divided by the proportion that were correctly predicted under the baseline model. It generally ranges from 0 to 1. Where a score of zero means no improvement over the baseline model and a score of 1 would mean that all of the unexplained cases from the baseline model are explained by the new model. In practice, the score can dip negative in rare cases where the baseline model actually outperforms less restrictive model with more covariates.

\(^{14}\)Other strategies are available. For example, the Bonferroni multiple comparisons correction adjusts the p-value for the number of tests conducted. However, this test is generally seen as too restrictive and is more helpful as a heuristic than an actual decision rule (Perneger, 1998). Other approaches based on the False Discovery Rate have been shown to be more theoretically sound (?). However for the purposes of this project, I opted for a different approach to assessing statistical significance based on permutation.
of fairness.”

Democrats went to great lengths in the floor debate to frame support for the bill as acting in the interests of families. The bill’s sponsor, Representative Carolyn Maloney (NY-14), said on the floor: “Members on both sides of the aisle talk about family values, but one of the most concrete ways we can help families is to give parents more time with their new children, without losing their paycheck.”

Table 2 shows the results of the regressions predicting Republican support for this bill. The first column shows the results of the regression with only the partisanship of the district. The second column shows the results when we add the moral foundations measures to the model.

The baseline model shows that district partisanship is strongly related to a member’s position on the bill. Members representing districts that went strongly for Bush in 2004 were more likely to vote against the bill than members representing more marginal districts. When we add the moral foundations measures, we can see that, independent of district partisanship, members who represented districts who scored particularly high on the Loyalty foundation were more likely to support the bill as well. Indeed, adding the moral foundations scores increases the predictive power of the model considerably.

Democratic Support for the Patriot Act Extension (see Medicare Physician Payment Reform Act)

To take another example, in a bizarre case of legislative maneuvering, the house considered a bill extending the Patriot act in 2009. This bill (H.R. 3961), which was confusingly called the Medicare Physician Payment Reform Act, extended several controversial programs that were set to expire. Ultimately, more than 90 percent of the Republican caucus supported the measure, but about 35 percent of the Democratic caucus voted against the bill. Table 3 shows the results of the vote for Democratic members.

The first column in the table shows that, within the Democratic caucus, members who represented the most Democratic districts were least likely to support the bill. The second column shows that this pattern persists once we account for the moral foundations of each district, but we also see that members who represent districts that place the most emphasis on the Care and Fairness foundations were significantly more likely to vote against the bill as well.

---


16Sen. Harry Reid “amended” the H.R. 3961 by striking its content entirely and replacing them with the Patriot act extensions.
Table 2: Regression Results: Parental Leave Act (Republicans only)

<table>
<thead>
<tr>
<th></th>
<th>Baseline Model</th>
<th>Moral Foundations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Care/Harm</td>
<td>0.055</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.105)</td>
<td></td>
</tr>
<tr>
<td>Fairness/Cheating</td>
<td>0.225∗</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.118)</td>
<td></td>
</tr>
<tr>
<td>Loyalty/Betrayal</td>
<td>0.296∗∗</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.120)</td>
<td></td>
</tr>
<tr>
<td>Respect/Subversion</td>
<td>−0.063</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.115)</td>
<td></td>
</tr>
<tr>
<td>Sanctity/Degradation</td>
<td>0.175</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.121)</td>
<td></td>
</tr>
<tr>
<td>District Partisanship</td>
<td>0.072∗∗∗</td>
<td>0.082∗∗∗</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Constant</td>
<td>−3.894∗∗∗</td>
<td>−4.372∗∗∗</td>
</tr>
<tr>
<td></td>
<td>(0.697)</td>
<td>(0.778)</td>
</tr>
</tbody>
</table>

Observations: 195 195
Log Likelihood: −97.184 −92.729
Akaike Inf. Crit.: 198.368 199.458

Note: ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01
Table 3: Regression Results: Patriot Act Extension (Democrats only)

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Baseline Model</th>
<th>Moral Foundations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Care/Harm</td>
<td>−0.237**</td>
<td>−0.237**</td>
</tr>
<tr>
<td></td>
<td>(0.103)</td>
<td>(0.103)</td>
</tr>
<tr>
<td>Fairness/Cheating</td>
<td>−0.259**</td>
<td>−0.259**</td>
</tr>
<tr>
<td></td>
<td>(0.109)</td>
<td>(0.109)</td>
</tr>
<tr>
<td>Loyalty/Betrayal</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>(0.097)</td>
</tr>
<tr>
<td>Respect/Subversion</td>
<td>−0.022</td>
<td>−0.022</td>
</tr>
<tr>
<td></td>
<td>(0.106)</td>
<td>(0.106)</td>
</tr>
<tr>
<td>Sanctity/Degradation</td>
<td>0.146</td>
<td>0.146</td>
</tr>
<tr>
<td></td>
<td>(0.102)</td>
<td>(0.102)</td>
</tr>
<tr>
<td>District Partisanship</td>
<td>−0.041***</td>
<td>−0.038***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.946***</td>
<td>2.828***</td>
</tr>
<tr>
<td></td>
<td>(0.445)</td>
<td>(0.467)</td>
</tr>
<tr>
<td>Observations</td>
<td>249</td>
<td>249</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−141.821</td>
<td>−136.402</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>287.642</td>
<td>286.804</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
Republican Support for the Water Quality Financing Act

Not all of the statistically significant findings could be easily interpreted. The above examples are relatively intuitive. It makes sense that Republicans who represent districts concerned with Loyalty and Fairness might be more amenable to arguments about parental leave that center around family values and creating government programs that reflect those that already exist in many private enterprises as Rep. Davis pointed out. It also makes sense that Democrats who represent districts with greater concern for Care and Fairness might be especially wary about extending the provisions of the Patriot act that are seen by many as violations of privacy and unfairly target already marginalized groups within American society.

In some cases however, the observed pattern could not be so readily understood. For example, the Water Quality Financing Act of 2007 drew votes from over 40 percent of Republican members. The main source of controversy in the bill seemed to be a provision that required any workers hired on federally funded water quality improvement projects to be paid a “local prevailing wage.” *A priori*, it would seem that fairness concerns should have dominated this debate. However, we see something different in the data. In Table 4, it is the Sanctity dimension that seems to be affecting voting behavior more than any other.\textsuperscript{17}

Sifting through the Noise

These are just a selection from the more than 1200 comparisons reported in this paper. How can we be sure that these are real effects and not just artifacts of making hundreds of comparisons? With so many statistical tests, we would expect more than a few “statistically significant” comparisons just by random chance. Classical statistical theory suggests that even if there were no relationship between these variables and elite behavior, we would see roughly $1274 \times 0.05 \approx 64$ significant findings at conventional levels. It would be surely possible to construct some plausible sounding story for at least some of these spurious results. What is needed is a strategy to sift through the “findings” returned by the regression results and submit them to more rigorous standards.

Permutation tests provide one straightforward robustness check. Permutation tests\textsuperscript{17}Given the results, a researcher interested in justifying the observed pattern in a *post hoc* fashion could try to make the Sanctity dimension fit here. Others have noted how environmentalists adopt Sanctity-laden language when talking about the necessity of protecting the environment (Feinberg and Willer, 2013). However, perusal of the relevant speeches in support of this bill did not support the idea that this kind of concern for the potential degradation of the environment was what was driving support for the bill.

\textsuperscript{16}
Table 4: Regression Results: Water Quality Financing Act (Republicans only)

<table>
<thead>
<tr>
<th></th>
<th>Baseline Model</th>
<th>Moral Foundations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Care/Harm</td>
<td>−0.012</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.105)</td>
<td></td>
</tr>
<tr>
<td>Fairness/Cheating</td>
<td>0.175</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.115)</td>
<td></td>
</tr>
<tr>
<td>Loyalty/Betrayal</td>
<td>0.054</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td></td>
</tr>
<tr>
<td>Respect/Subversion</td>
<td>0.189</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.117)</td>
<td></td>
</tr>
<tr>
<td>Sanctity/Degradation</td>
<td>0.234**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.116)</td>
<td></td>
</tr>
<tr>
<td>District Partisanship</td>
<td>0.070***</td>
<td>0.091***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Constant</td>
<td>−3.295***</td>
<td>−4.283***</td>
</tr>
<tr>
<td></td>
<td>(0.614)</td>
<td>(0.728)</td>
</tr>
<tr>
<td>Observations</td>
<td>187</td>
<td>187</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−112.493</td>
<td>−105.479</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>228.986</td>
<td>224.958</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
work by using the observed data to create realistic null distributions that can be used to compare against the results obtained. The explanatory variables are randomly ordered, and the test is rerun with this randomized data. The randomization of the data means that we should expect null results from any statistical test applied. This permutation procedure is repeated many times (modern computing power means that it is usually easy to repeat the test hundreds or thousands of times), and we compare the distribution of test statistics in the permuted data to the observed test-statistic in the original data. This new distribution of test statistics provides a meaningful baseline against which we can compare the original results.

In my case, I am interested in understanding whether anything is added by including the moral foundations measures. To conduct the permutation tests, I randomly order the row subscripts of the congressional district level moral foundations matrix and repeatedly run regressions with the permuted data. By permuting the values of the moral foundations measures, we can get a sense of the probability that we would see patterns at least as extreme as those we observe in the tests against a more realistic null distribution than that implied by the classical hypothesis test. In Figure 2, I show the distribution of PRE statistics obtained from 10,000 regressions with different permutations of the moral foundations scores for each of the three different roll call votes discussed above. The vertical lines show the PRE from the un-permuted data. For the parental leave bill and the Patriot act extension, the PRE score from the un-permuted data was much more extreme than what was observed in the permuted datasets. This is taken as evidence that the findings in these two cases are robust. In the water quality bill, the observed improvement of model fit with the original data is not out of the norm for randomly ordered data. This finding is more likely to be spurious.\footnote{See Appendix D for some simulations showing the efficacy of this procedure. The results show that this permutation strategy is somewhat conservative. In simulated cases where there is a true effect, the permutation analysis rejects true findings more than 20% of the time. On the other hand, the procedure very rarely leads to Type 1 errors (failing to reject the null hypothesis when it is in fact true).}
Figure 2: Distribution of PRE scores obtained from 10,000 permutations of the moral foundations matrix. The vertical line shows the PRE from the unpermuted data for the three example cases. In the case of the Paid Family Leave Act (a) and the Patriot Act extension (b), the observed increase in model fit was much larger than what would have been predicted by chance. In the case of the Water Quality Financing Act (c), the increase in model fit was not significantly greater than what might have been observed by random chance.
All Votes

I repeated the above procedure (measuring how much the model fit increased when adding the moral foundations measures and then permuting the moral foundations matrix to test the robustness of the relationship) for all of the 1200+ votes under consideration. Figures 3 and 4 show the results for the votes within the Republican and Democratic parties respectively. In each figure, the horizontal axis shows the proportion of the permutation tests that returned PRE statistics greater than the actual data (e.g. randomly ordering the moral foundations measures actually performed better than the unpermuted data). In cases where the permuted datasets performed consistently more poorly than the original data, we can be more confident that the observed effect is not just an artifact of the data.

Figures 3 and 4 reveal the importance of these kinds of efforts toward addressing multiple comparisons when conducting hundreds of statistical tests. Most of the apparent findings in the data are suspect. This is true in many instances where adding the moral foundations measures to the regression seems to substantially boost the performance of the model (e.g. PRE > 0.1).

After culling out spurious correlations with the permutation procedure, about 17% of the roll call votes under consideration showed robust effects from adding the moral foundation measures. This rate was relatively constant across both parties (17.6% for Democrats, 16.8% for Republicans). This one-out-of-six figure is not trivial given the number of factors that affect roll call votes and the tremendous share of the variation that was already accounted for in district partisanship. In the remainder of this section, I examine how this baseline proportion of “moral votes” varies by partisanship, majority/minority status, and across the different foundations.
Figure 3: Plot of PRE scores for votes that split the Republican party. The horizontal axis shows the results of the permutation tests; namely, the proportion of permuted datasets that returned PRE scores higher than the PRE score obtained from the unpermuted data. The vertical axis shows the PRE score from the unpermuted data. The vertical line shows those tests where less than 5% of the permutations returned scores higher than the original data. Blue points correspond with votes that were taken while the Democrats held a majority (red points for Republican majority).
Figure 4: Plot of PRE scores for votes that split the Democratic party. The horizontal axis shows the results of the permutation tests; namely, the proportion of permuted datasets that returned PRE scores higher than the PRE score obtained from the unpermuted data. The vertical axis shows the PRE score from the unpermuted data. The vertical line shows those tests where less than 5% of the permutations returned scores higher than the original data. Blue points correspond with votes that were taken while the Democrats held a majority (red points for Republican majority).
Table 5: Numbers of Robust and Statistically Significant Relationships by Party

<table>
<thead>
<tr>
<th></th>
<th>Republicans</th>
<th>Democrats</th>
</tr>
</thead>
<tbody>
<tr>
<td>Care</td>
<td>19</td>
<td>30</td>
</tr>
<tr>
<td>Fairness</td>
<td>31</td>
<td>35</td>
</tr>
<tr>
<td>Loyalty</td>
<td>27</td>
<td>10</td>
</tr>
<tr>
<td>Respect</td>
<td>45</td>
<td>22</td>
</tr>
<tr>
<td>Sanctity</td>
<td>69</td>
<td>42</td>
</tr>
</tbody>
</table>

A closer examination of the particular moral dimensions that mattered for each party (determined by looking at the particular foundation or foundations that were statistically significant for the subset of robust cases) shows that, relative to their Republican colleagues, Democrats were more often affected by the Care and Fairness dimensions. Table 5 shows the counts of statistically significant coefficients for each moral foundation (again, only among the subset of robust relationships) by party. For example, the first row of the table shows that there were 19 bills that showed a robust statistically significant relationship between constituent emphasis on the Care foundation and variation in voting with the Republican caucus. Correspondingly, there were 30 bills that showed a similar relationship within the Democratic caucus between the Care foundation and roll call voting. Although partisans do appear to be differentially responsive to constituent moral concerns (with Democrats seemingly more responsive to Care and Fairness concerns and Republicans paying more heed to Loyalty, Respect, and Sanctity concerns), members from both parties showed at least some level of responsiveness across all of the different domains.

**When Morality Matters**

The results from the previous section showed that in a substantial number of cases the moral foundations allow us to better understand congressional voting behavior. In this section, I will turn my attention to the question of the conditions that make these “moral votes” more likely to occur. I expect to find a role for the moral foundations when party pressure is low. To investigate the conditions under which we might expect to see “moral votes,” I used the results from the previous section to create a dichotomous indicator for whether or not a vote was substantially affected by constituent moral concerns. This variable takes a value of 1 for votes that showed a robust increase in model fit from adding the moral foundations measures (e.g. less than 5% of the permuted datasets had a better fit than the unpermuted data). Tables 6 and 7 show some summary results for the
proportions of moral votes by majority status and the result of the vote.

Table 6: Republicans: Proportions of moral votes by majority status and vote result

<table>
<thead>
<tr>
<th>Result</th>
<th>P(Moral)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Majority Failed</td>
<td>0.14</td>
</tr>
<tr>
<td>Minority Failed</td>
<td>0.24</td>
</tr>
<tr>
<td>Majority Passed</td>
<td>0.08</td>
</tr>
<tr>
<td>Minority Passed</td>
<td>0.20</td>
</tr>
</tbody>
</table>

Table 7: Democrats: Proportions of moral votes by majority status and vote result

<table>
<thead>
<tr>
<th>Result</th>
<th>P(Moral)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Majority Failed</td>
<td>0.03</td>
</tr>
<tr>
<td>Minority Failed</td>
<td>0.14</td>
</tr>
<tr>
<td>Majority Passed</td>
<td>0.18</td>
</tr>
<tr>
<td>Minority Passed</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Given the majority party’s control over the agenda in the contemporary House, I expect party pressure to be higher for members of the majority party. The results in the tables confirm that expectation. Independent of a bill’s prospects (as measured by post facto performance), members in the majority were less likely to be significantly affected by their constituents’ moral concerns. Interestingly, Republicans seemed to be under the most pressure to bow to the party’s wishes on bills that ultimately passed the house, while Democrats seemed to be under more pressure on bills that ultimately failed to pass.

Including additional information about the bills under consideration in a multiple regression framework (e.g. controls for substantive issue content, dummy variables for the specific congress, and the proportion of each party that supported the bill), does not alter the pattern revealed in the table above. Members in the minority appear to be more often in positions where their votes are affected by their constituents moral foundations rather than the dominant dimension of conflict in Congress.

Discussion and Conclusion

In this chapter, I have shown a significant relationship between constituency moral foundations and congressional voting behavior in some instances. This was true even after

---

19Issue area information was taken from the Congressional Bills Project “Major Issue” codes available here: http://www.congressionalbills.org/.
20Full regression results can be found in Appendix E
controlling for the partisan complexion of the district (a factor which explains the lion’s share of variance in roll call votes). In more than one in six roll-call votes, there appeared to be a statistically significant and robust relationship between constituent moral concerns and their representatives’ roll call votes. This relationship was, perhaps paradoxically, strongest for members of the minority party. Members in the minority appear to be more free to vote their districts’ preferences. For a large number of votes, members of congress seem to be responsive to their constituents’ moral concerns.

Despite this apparent responsiveness, the results I have presented in this chapter hold some troubling implications for normative theories about democracy and representation. The precise moment when one’s preferred party has assumed power and is in a position to implement policy changes is also the moment when one’s representative is under the most pressure to ignore her constituency’s preferences. This result might go part of the way toward explaining the extreme dissatisfaction that most people seem to have with governmental institutions.

One unanswered (and unanswerable given the data here) question relates to the precise mechanism by which constituent moral foundations affect congressional voting behavior. I have presented some evidence here that they matter in some cases, but we know from the literature on political interest and attention at the individual-level that members of the general public pay little to no attention to specific roll-call votes.

There are several potential avenues. First, it may be the case that individuals select candidates based (in part) on the extent to which their moral values align. In Chapter 3, I presented some evidence that this appears to be the case for presidential voting. It would not be too far of a stretch to apply that same logic to voting for and against members of congress. Second, Tracy Sulkin’s work (2005; 2011) shows how challengers can be instrumental in holding incumbents to account for deviating too far from district preferences. Perhaps, legislators who anticipate (or have had recent experience with) challengers who might better represent the moral concerns of their constituents adjust their behavior accordingly.

Another interesting question which the data in this chapter unfortunately cannot answer is the extent to which the patterns shown here are time-bound. Measures of the moral foundations do not exist prior to 2007, but it is interesting to speculate about what the picture would look like if we had access to comparable measures of constituent-level moral concern going back fifty years. In a less polarized party system, would the moral foundations of constituents serve as a more powerful constraint on elite behavior?

In the next chapter, I will explore some of these questions by looking at moralized
political rhetoric over the past 35 years. Lacking reliable survey-based measures of the moral foundations prior to the mid-2000s, I will not be able to specifically determine to what extent responsiveness to constituent moral considerations has or has not changed over time, but the patterns in moral language use between and within each of the major parties will help to fill out the overall picture of the role of predispositions in politics by showing the ways in which elites attempt to frame political controversies in ways more favorable to their own positions.
References


Appendices

A Estimating Partisanship and Ideology

For my purposes, I adapt the MRP method to include multiple sources of data. Specifically, I am interested in correcting for the partisan and ideological biases of the sample in addition to the demographic imbalances. The approach is a straightforward two-stage application of MRP. First I will use an independent source of data (actually several sources) to estimate the partisan and ideological leanings of each cell in the data and use the expanded cell space to generate estimates of the moral foundations.

Stage 1: Partisanship and Ideology

I use an aggregation of Pew surveys and data from the CCES to estimate partisanship and ideology.\(^\text{21}\) This is a straightforward application of MRP methods that have been described elsewhere (e.g. Lax and Phillips (2009)). I stratify on age (3 categories), sex, education (2 categories; less than college, college), race (2 categories, non-Hispanic White, other), income (2 categories; less than $50k, more than $50k), and 436 congressional districts (including D.C.).\(^\text{22}\) In addition to the demographic cells, I also stratify based on the source of the data (Pew or CCES).\(^\text{23}\) This yields 436 * 3 * 2 * 2 * 2 * 2 = 41856 cells.

The model looks like this:

\[
y_{i.} \sim \text{Multinomial}(p_{i.}, n_{i})
\]

\[
p_{ij} = f(\beta_{ij}^{\text{age}} + \beta_{ij}^{\text{sex}} + \beta_{ij}^{\text{race}} + \beta_{ij}^{\text{income}} + \beta_{ij}^{\text{CD}} + \beta_{ij}^{\text{source}})
\]

\(^{21}\)I collected every nationally representative survey that I could find between 2001 and 2011 from the Roper iPoll database conducted by Pew (\(n > 164,000\)). The CCES data are from the common content administered in 2008, 2009, 2010, 2011, and 2012 (\(n > 176,000\)).

\(^{22}\)While the CCES includes information on respondents’ congressional districts, the Pew data does not. In many cases, the Pew datasets did include respondent zip codes, and in a few cases where zip codes were not available, the data included county information. There is not a perfect correspondence between zip code and congressional district (about 30% of respondents lived in a zip code that was split between two or more congressional districts), and in the case of counties the correspondence is significantly worse. In cases where the geographic data was ambiguous, respondents were assigned to congressional districts probabilistically based on the proportion of the geography that falls into each district. For example, if a county is split between three congressional districts such that 60% of the county falls into one district and 30% into another and 10% into a third, that individual was assigned to each district with a probability of 0.6, 0.3, and 0.1 respectively. These proportions were calculated with the help of the (tremendously useful) GeoCorr website hosted by the University of Missouri (http://mcdc.missouri.edu/websas/geocorr12.html).

\(^{23}\)This seems especially important given the dramatically different modes employed by the two surveys. The Pew surveys were all nationally representative telephone surveys, and the CCES is an opt-in internet survey.
The dependent variable \( y_{ij} \) holds a count of the number of people identifying as, for example, “liberal” and “Democrat” in cell \( i \). There are nine possibilities corresponding with the \( 3 \times 3 \) tabulation of ideology (liberal, moderate, conservative),\(^{24}\) and partisanship (Democrat, independent, and Republican).\(^{25}\) For example, in the combined Pew data, there were 15 people who were white, male, under 30, with less than a college degree, making less than $50,000 dollars per year living in Alabama’s 1st District. Of these 15 individuals, none identified as liberal Democrats, 3 identified as moderate Democrats, and 1 identified as a conservative Democrat. The model “borrows strength” from similar cells (e.g. the political identifications of other young, white, males in Alabama), and tells us that we should expect about 3% of individuals who match these demographics in the population to identify as liberal Democrats, 10% to identify as moderate Democrats and a little less than 5% as conservative Democrats.

The model was fit in JAGS (Plummer et al., 2003) with vague hyperparameters for the \( \beta \) parameters.\(^ {26}\) Separate models were estimated for the partisan-ideological breakdown in the pre-2011 redistricting districts and the post districting districts. These cell proportions will be used in the next stage of the model to stratify additionally on ideology and partisanship.

We can check the face-validity of the model by looking at the correlation between estimates of district partisanship and ideology with presidential vote. This is accomplished easily enough by projecting the cell estimates onto a comparable set of population estimates. I use the 2008-2011 American Community Survey to get estimates of the populations of each cell in the model.\(^ {27}\) The estimates of district partisanship and ideology correlate strongly with the presidential vote at the congressional district level (e.g. the post-districting estimated proportion of Democratic identifiers in a district correlates with Obama’s 2012 share of the two party vote at \( r = 0.69 \)).

---

\(^{24}\)People who responded “Don’t Know” or refused to respond were classified as “moderate.”

\(^{25}\)People who responded “Don’t Know,” “Other,” or refused to respond were classified as independents. People who said they “leaned” toward one party or the other were classified as independents as well.

\(^{26}\)See Appendix B for the JAGS code used. After discarding the first 1,000 iterations, the next 1,000 iterations were retained as an approximation of the posterior distribution. Visual inspection of the chains suggests that the models had converged on the appropriate solution.

\(^{27}\)As with the survey data, there is not a perfect correspondence between the level of geography available in the ACS (public use microdata areas [PUMAs]) and the congressional district. There are 2,069 PUMAs in the ACS many of which fall entirely within one congressional district. For PUMAs that spilled into multiple congressional districts, I assigned individuals to congressional districts probabilistically based on the proportion of the population of the PUMA that lives in each district.
Stage 2: Moral Foundations

I follow a very similar procedure for estimating the moral foundations of each district. In the second stage model, I include fewer demographic categories to keep the number of cells to a more manageable level. The model includes 3 categories of partisanship (Democrat, independent, Republican), 3 categories of ideology (liberal, moderate, conservative), 2 categories of education, sex, a questionnaire indicator, and 436 congressional districts (plus D.C.). This yields $3 \times 3 \times 2 \times 2 \times 436 = 31,392$ total cells.

The model for the moral foundations was slightly different. In the partisanship and ideology case, I had counts that were modeled as being multinomially distributed. In the moral foundations case, I have cell averages of the moral foundations scores. Again, the model was estimated in JAGS and the code can be found in Appendix B. I projected the estimates from the model onto the population data to produce estimates of each of the moral foundations at the congressional district level.

$$m_{ij} \sim \text{Normal}(\mu_{ij}, \sigma_j / \sqrt{n_i})$$

$$\mu_{ij} = \beta_{ij}^{\text{Party}} + \beta_{ij}^{\text{Ideo}} + \beta_{ij}^{\text{Sex}} + \beta_{ij}^{\text{Educ}} + \beta_{ij}^{\text{CD}} + \beta_{ij}^{\text{source}}$$

In the second stage, the dependent variable ($m_{ij}$) holds the average of the moral foundations score for all of the individuals in a particular cell. This average is considered to be drawn from a normal distribution centered at $\mu_{ij}$ and with a standard deviation that is

---

28 Including all of the demographic categories in the second stage would lead to a model with nearly 190,000 cells. This is a larger number of cells than I have data, and it would make the results too dependent upon the model.

29 The data mostly come from the large database of responses to the MFQ30 collected at YourMorals.org. However, a subset of the data include responses from the MFQ48. The MFQ48 includes all of the items from the MFQ30 with an additional 18 that were designed to address some shortcomings in the estimation of the fairness domain in particular. In Chapter 2 I discuss how the MFQ30 and MFQ48 scale together at great length.

30 Chapter 2 details the response model that was used to extract latent parameters from individual responses to the Moral Foundations Questionnaire. In that chapter, I discuss some of the limitations of the standard procedure to scaling the MFQ (namely adding up responses to items that have been assigned a priori to a particular dimension), and propose a new method that allows items to load onto multiple dimensions. I show that the new measure fits the responses better than alternative measures and produces estimates of moral concern that perform better than other measures.

This measurement model is the foundation for the aggregate measures relied upon in this chapter. After using a subset of responses from the larger database to estimate the item parameters in the model, I estimated the latent moral concern parameters for the remaining respondents from the large YourMorals.org database. This was accomplished through a simple optimization procedure to find the values of the latent “ability” parameters that maximized the likelihood of observing an individual’s response pattern conditional on the item parameters.

The resulting estimates display the same characteristics as those explored in Chapter 2. The estimates of the moral foundations are less correlated with one another, and the measures perform measurably better in terms of their relationship with politically relevant dependent variables.
a function of the number of individuals in the cell.\textsuperscript{31} As in the party-ideology model, the main parameter of interest is decomposed into several different parts (party, ideology, geography, etc.). In practice, this means our cell estimates will be borrowing strength from similar cells.

\section*{B JAGS Code}

The first stage model was fit to a collection of Pew surveys and CCES surveys described in the main body of the text. These surveys used roughly comparable partisanship and ideology items and included all of the necessary demographics. The estimated parameters from the model were used to generate estimates of the proportion of individuals in each cell who identified with a particular party and ideology in order to incorporate these variables into the second stage model to estimate the moral foundations at the Congressional District level.

\begin{verbatim}
model {

  for (j in 1:N.cells) { #loop through the non empty cells

    y[j,1:9] ~ dmulti(p[j,1:9], n[j]) #party-ideology is distributed #multinomial conditional on the cell probabilities and the number of #respondents in each cell

    for (k in 1:9) { #loop through the 9 possible response options

      p.star[j,k] <- exp(b.cd[cd[j],k] + #exponentiate to ensure #positive results

      b.sex[sex[j],k] +
      b.ed[ed[j],k] +
      b.race[race[j],k] +
      b.inc[inc[j],k] +
      b.src[src[j],k] +

      This is the central limit theorem in action. The standard deviation of our prediction is decreases with the square root of the sample size, and it is mathematically equivalent to running the much more computationally intensive model with the individual scores rather than the grouped means.

33

\end{verbatim}
b.age[age[j],k])
"

p[j,1:9] <- p.star[j,1:9]/sum(p.star[j,1:9]) #divide by the sum to
#ensure probabilities sum to 1
"

for (k in 1:9) {
for (j in 1:51) {
alpha0[j,k] ~ dnorm(0, 1) #state effects
}

for (j in 1:CD) {
b.cd[j,k] ~ dnorm(alpha0[state[j],k], .1) #CD effects
}

for (j in 1:2) { ##other demographic effects
b.sex[j,k] ~ dnorm(0, .1)
b.ed[j,k] ~ dnorm(0, .1)
b.race[j,k] ~ dnorm(0, .1)
b.inc[j,k] ~ dnorm(0, .1)
b.src[j,k] ~ dnorm(0, .1)
}

for (j in 1:3) { #age effects
b.age[j,k] ~ dnorm(0, .1)
}
}

C Estimating Moral Foundations

The stage two model was similar:

model {
for (j in 1:N.cells) { #loop through non-empty cells
for (k in 1:5) { #loop through the five moral foundations

34
\[
\theta_{j,k} \sim \text{dnorm}(\mu_{j,k}, n[j]\times\tau[k]) \quad \text{JAGS uses the precision, so rather than dividing by the square root of } n, \text{ we multiply by } n
\]

\[
\mu_{j,k} \leftarrow b.\text{party}[\text{party}[j],k] + b.\text{ideo}[\text{ideo}[j],k] + b.\text{sex}[\text{sex}[j],k] + b.\text{educ}[\text{educ}[j],k] + b.\text{src}[\text{src}[j],k] + b.\text{cd}[\text{cd}[j],k]
\]

for (k in 1:5) { # 5 Moral Foundations
  tau[k] \sim \text{dgamma}(.1, .1) \quad \text{Precision parameters}
  for (j in 1:2) { # demographic effects
    b.\text{sex}[j,k] \sim \text{dnorm}(0, .1)
    b.\text{educ}[j,k] \sim \text{dnorm}(0, .1)
    b.\text{src}[j,k] \sim \text{dnorm}(0, .1)
  }
  for (j in 1:3) {
    b.\text{party}[j,k] \sim \text{dnorm}(0, .1)
    b.\text{ideo}[j,k] \sim \text{dnorm}(0, .1)
  }
  for (j in 1:436) { # CD effects clustered by state
    b.\text{cd}[j,k] \sim \text{dnorm}(b.\text{state}[\text{state}[j],k], .1)
  }
  for (j in 1:51) { # State hyperparameters clustered by region
    b.\text{state}[j,k] \sim \text{dnorm}(b.\text{region}[\text{region}[j],k], .1)
  }
  for (j in 1:9) { # Region parameters
    b.\text{region}[j,k] \sim \text{dnorm}(0, .1)
  }
}
}
D Monte Carlo Simulations on the Efficacy of the Permutation Test

To evaluate the performance of the permutation test, I conducted a simple simulation. Using the observed partisanship and moral foundations measures for the Republicans from the 110th Congress, I simulated a set of roll call votes as follows:

\[ y_{ij} = I([\alpha_j + X_i \beta_j + \delta_j * \text{partisanship}_i + \zeta_j * z_i + \epsilon_{ij}] > 0) \]

Each vote is simulated as a function of constituent moral foundations (the \( X_i \) matrix), district partisanship, and a set of unobserved factors (\( z_i \)). In the simulations, \( \alpha_j \) is set to zero, \( \zeta_j \) is drawn from a standard normal distribution for each simulated vote, and the \( z_i \) factors are drawn from a standard normal distribution for each legislator. For half of the simulations, the \( \beta_j \) vector was set to zero, and the other half set one of the values of the vector to 0.5. The true value of the \( \delta_j \) was set to 1 (different values of the parameters return substantively similar results). So, for half of the simulated votes there was a true effect of one of the moral foundations that was half the magnitude of the partisanship variable. For the other half of the votes, there was no effect of the moral foundations on voting behavior.

With each simulated vote, I ran a regression including district partisanship and the moral foundations measures. I retained only the simulated votes where the regressions returned a significant coefficient for at least one of the moral foundations measures.\(^{32}\) The procedure was repeated until I had 1500 votes with a “true” effect for one of the moral foundations measures, and 1500 votes with an apparent (although spurious) effect for one of the moral foundations measures.

I then applied the permutation method described in detail in the main text of the chapter to each of these votes. It is a simple matter to tabulate the proportions of true and spurious votes that were identified as true effects with the robustness procedure. Figure 5 shows the results graphically. The plot shows the density of significance values (proportion of permuted datasets that returned a PRE value greater than the original data). The solid line shows the density for regressions where there was a true effect of the moral foundations, and the dotted line shows the density for the set of regressions with no true effect of the moral foundations.

Figure 6 shows the PRE scores plotted against the significance scores of the permutation tests (similar to Figures 3 and 4 in the main text) for the simulated data. The panel

---

\(^{32}\)This was accomplished by sampling the \( \epsilon_{ij} \) repeatedly until a regression returned a set of coefficients where one of the elements of the \( \beta_j \) vector was significant and greater than 0.33.
Figure 5: Densities of permutation test values for regressions with a true effect (solid line) and those without a true effect (dotted line) of the moral foundations.
on the left shows the results of the simulations for regressions with true effects and the right-hand panel shows the same for the regressions without true effects. In the 1500 cases where there was a true effect, the test correctly identified the effect in 75.9% of the time. For the other 1500 cases where there was no true effect (although the regressions returned a statistically significant coefficient), the permutation test correctly identified rejected the findings more than 80% of the time. In just 17% of the cases, the permutation test failed to reject a spurious relationship.

Figure 6: Plot of PRE scores for simulated votes. The horizontal axis shows the results of the permutation tests; namely, the proportion of permuted datasets that returned PRE scores higher than the PRE score obtained from the unpermuted data. The vertical axis shows the PRE scores from the unpermuted data. The vertical line shows those tests where less than 5% of the permutations returned scores higher than the original data. The red dots show points that were erroneously classified as not significant when there was a true effect (in the left panel) and those that were erroneously classified as significant when there was no effect (in the right panel).

Finally, Figure 7 shows a ROC curve for the permutation tests in the simulated data. The line shows how the rates of true positives and false positive are related to one another for different significance thresholds.
Figure 7: The relationship between the rate of false positives and the rate of true positives for different significance levels. The points on the plot show the 0.01, 0.05, and 0.1 levels. At the 0.05 level (that chosen for the analyses in this chapter), the rate of true positives is about 76% and the false positive rate is about 17%.
### Supplementary Regression Results

Table 8: When Morality Matters: Probit Models

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Democrats</th>
<th>Republicans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Majority</td>
<td>−1.253**</td>
<td>−0.918***</td>
</tr>
<tr>
<td></td>
<td>(0.533)</td>
<td>(0.257)</td>
</tr>
<tr>
<td>Passed House</td>
<td>0.367**</td>
<td>−0.095</td>
</tr>
<tr>
<td></td>
<td>(0.186)</td>
<td>(0.151)</td>
</tr>
<tr>
<td>Democratic Support</td>
<td>−0.091</td>
<td>−0.100</td>
</tr>
<tr>
<td></td>
<td>(0.531)</td>
<td>(0.131)</td>
</tr>
<tr>
<td>Republican Support</td>
<td>−0.505**</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>(0.197)</td>
<td>(0.388)</td>
</tr>
<tr>
<td>Majority*Passed</td>
<td>0.707</td>
<td>−0.160</td>
</tr>
<tr>
<td></td>
<td>(0.553)</td>
<td>(0.249)</td>
</tr>
<tr>
<td>Constant</td>
<td>−0.312</td>
<td>−0.439</td>
</tr>
<tr>
<td></td>
<td>(0.596)</td>
<td>(0.519)</td>
</tr>
<tr>
<td>Observations</td>
<td>467</td>
<td>809</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−187.693</td>
<td>−339.502</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>431.386</td>
<td>737.005</td>
</tr>
</tbody>
</table>

*Note:* 
*p<0.1; **p<0.05; ***p<0.01

Models include controls for substantive issue area and the congress.