Partisan Feedback:

Heterogeneity in Opinion Responsiveness*

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Abstract

Do partisans respond differently to changes in public policy depending on which party controls the government? It is well established that opinions of various groups tend to move in parallel over time; however, work on partisanship shows that partisans can respond very differently to the same message. In this paper, I investigate whether partisans from different parties react the same to changes in policy, the implication of the parallel publics literature, or differently, as literature on partisanship would imply. I argue that we should see important differences in policy feedback between partisan groups, but only on salient policies that have large disagreement across partisan lines. To test this, I use the thermostatic model of opinion-policy feedback, relying on data from the 1973–2014 General Social Survey. Findings indicate that partisans react differently to policy in high-salience issue areas with relatively large disagreement. I conclude by discussing some of the implications of these findings for research on public opinion and public policy.

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1 Introduction

Research by political scientists demonstrates that public policy responds to public opinion. These policy changes in turn create a feedback loop where the public eases its current demands when governments move in the direction of their previous ones (for examples, see Wlezien 1995; Erikson, MacKuen, and Stimson 2002; Soroka and Wlezien 2010). This has important implications for the role of public opinion in democracies, as it indicates that the public responds to policy changes, and that policy changes in response to public opinion.

However, all previous studies have made an assumption that may not be warranted. They assume that all members of the public react to policy changes in parallel. Given the consistent findings of "parallel publics" by Page and Shapiro (1992) and others, this assumption may be reasonable. However, it runs in the face of considerable research showing that partisanship colors perceptions and preferences (Angus Campbell et al. 1960; Erikson, MacKuen, and Stimson 2002; Soroka and Wlezien 2008; Enns and Kellstedt 2008; Johnson and Kellstedt 2013; Gonthier 2016).

In this paper, I identify three specific mechanisms that should all lead to partisan differences in policy feedback. Specifically, in comparison to other voters, supporters of the incumbent party a) may not monitor government action as carefully, b) may process information differently, and c) may change their preferences to align with government policy. All three predict that responsiveness is heterogeneous, with supporters of the incumbent party being less responsive.

In the next section, I briefly review what we know about policy feedback, and then explain how each of the three mechanisms impact specific elements on the model, yielding a testable hypothesis. I then qualify this hypothesis further, by suggesting that it will be more evident in highly polarized, salient issues. I then test these expectations using opinion and policy data from the United States from 1973 to 2014.

2 Opinion Responsiveness

Changes in public policy can produce changes in public opinion. If government increases the amount of policy, then fewer people prefer further increases of that policy. This logic underlies the thermostatic model, which helps us understand how policy changes affect opinion. Spending on a particular policy changes, and the effect of that change is observed on aggregate relative preferences. This relationship has been studied extensively at the national level in the US (Wlezien 1995; Ellis and Faricy 2011), the U.S. state level (Pacheco 2013b), as well as cross-nationally (Soroka and Wlezien 2010).

Of course, the thermostatic model is a subset of the more general policy feedback literature. Whereas the thermostatic model expects a negative relationship between policy and opinion, this is not always the case. Sometimes, we observe positive feedback; that is, the more policy people get, the more they want (Pacheco 2013a). Individuals' reactions to policy can also depend on context. For example, individuals' support for immigration depends on policy (the amount of immigration), but that appears to be conditional on context (the level of segregation in their area) (Rocha and Espino 2009). Other times, the public does not respond at all to policy change (Soss and Schram 2007; Wlezien 2016). Policies can also affect political behavior (for a review of recent literature, see Andrea Campbell 2012). In this paper, we will focus on the thermostatic model, but it should be kept in mind that there are other ways that policy can affect opinion and behavior.

Studying the opinion-policy loop requires measurements of people's preferences. We usually ask people their relative preferences (for more or less policy) rather than their absolute preferences (an amount of policy) due to the complicated nature of decisions and choices in politics. For example, while naming an exact dollar amount they want the government to spend on national defense is probably outside the capacity of most people, giving a relative preference — whether they prefer more or less than what the government is spending currently — is a much less demanding task. These survey questions generally ask people whether they think we're spending too much, about the right amount, or too little across several different policy areas.

I follow previous literature in conceptualizing individuals' relative preferences R for more or less spending as being the difference between their absolute preference P^* and where they think policy P currently is. This relationship is captured in Equation 1. Of course, when we measure R, the responses we get are a trichotomous outcome — "more," "less," or "about the same."

$$R = P^* - P \tag{1}$$

Relative preferences (R) depend on two things: both what an individuals' preferred policy position is (P^*), as well as where policy is now (P). This logic is at the heart of the opinion-policy feedback loop. Given absolute preferences, if policy changes, then relative preferences should change in the opposite direction. In other words, if spending goes up (P increases) and absolute preferences do not change (P^* remains constant), then an individual should be more likely to say that there is too much spending (R will decrease).

The standard feedback model usually takes a form similar to Equation 2:

$$R_{ij} = \beta_0 + \beta_1 P_{ij} + \beta W_{ij} + \varepsilon_{ij} \tag{2}$$

where R represents individual i's relative opinion (see Equation 1) for more or less spending on policy j. Although the thermostatic model is usually modeled at the aggregate level Wlezien and Soroka (see 2014, for one analysis at the individual level using welfare), we will model it at the individual level, since the theoretical mechanisms behind partisan feedback operate at the individual level.[1] P represents the dollar amount spent and W represents a vector of variables meant to capture P^* since P^* is not directly observable.[2] β_1 gives us information about the effect of policy on opinion. Negative values are evidence that as spending on a policy increases, people are less likely to prefer additional spending.

[1]Wlezien and Soroka (2014) analyzes the thermostatic model at the individual level rather than the aggregate, though for a single policy area (welfare).

[2]The β term associated with W is a vector of coefficients.

2.1 The Role of Partisanship

Partisanship is oftentimes a moderating variable in the kinds of relationships political scientists tend to study. People tend to form their partisan attachments young, and to interpret a lot of information with partisan "lenses" on (Angus Campbell et al. 1960). Partisanship affects other areas of life as well, such as happiness (Pierce, Rogers, and Snyder 2016), trust in government (Keele 2005), and preference formation (Mullinix 2016; Lerman and McCabe 2017). Furthermore, there is evidence that partisanship may actually *cause* (some of) people's political beliefs, even if the exact mechanism is unclear (Gerber, Huber, and Washington 2010).

What we already know about partisanship suggests that partisans should react differently to policy changes. However, they should react based not on an individual's party, but rather party control of government. We know, for example, that party control of government influences individuals' trust of particular institutions (Gershtenson, Ladewig, and Plane 2006). This has important implications for opinion change. If a person's fellow partisans have control over the government, we should see *less* responsiveness to policy changes. And, inversely, if the opposite party controls the government, we expect those people's opinions to be *more* responsive to policy change.

There are several possible mechanisms at work here. If we conceptualize relative preferences as the difference between absolute preferences and policy (as in Equation 1), then differences in the thermostatic model must arise from either differences in changes in policy or changes in preferences. I discuss both of these possibilities in turn, starting with changes in policy.

2.1.1 Explanation 1: Changes in Policy

One possibility is that partisans differ in P — policy. Of course, in a certain sense this makes no sense; there is a single dollar amount spent by the U.S. on defense each year. We do know, however, that in other domains where there is a "correct" answer, partisan differences can emerge (Bartels 2002; Gerber and Huber 2010). So when we discuss differences in changes in policy (ΔP_t), we are really talking about differences in people's beliefs about where policy is. Phrased alternatively, partisan groups have differing beliefs about the magnitude and/or direction of policy change. In this section, I propose two different mechanisms that could be at work here: differences in monitoring and differences in information processing.

Partisan groups could be more likely to monitor the government's actions if the government is controlled by the opposite party. In other words, these groups are more attentive to changes in P. It seems likely that partisan groups monitor the government's policy changes at different levels depending on the partisan makeup of government.

The logic here is simple. Once your party has control of government, you can "relax" — your job is done and you trust your fellow partisans in government to get the job done (Keele 2005; Gershtenson, Ladewig, and Plane 2006). Conversely, if your party loses and is out of government, you may feel the need to increase your watchfulness of what the government is doing.

If this is the case, then "in-partisans" and "out-partisans" may update their beliefs about the location of P differently from one another. In other words, they can differ in how they update their beliefs about the magnitude and/or direction of change in P. Since policy today (P_t) is simply the sum of yesterday's policy (P_{t-1}) and whatever changed (ΔP_t) if people fail to observe ΔP_t then they will not adjust their opinions thermostatically.[3] While total failure to pay attention to policy change is an extreme case, especially if the issue is at least somewhat salient, it could be the case that in-partisans may be less observant of governmental actions on average than out-partisans.

Differences in monitoring (i.e. the reception of information about policy change) can produce differences in thermostatic feedback. However, another plausible mechanism is that the *same* information may be considered differently by partisan groups. Partisans may disagree on the magnitude (or direction) of policy change; Republicans in the electorate may view policy changes by Democrats in government as being large, whereas Democrats in the

[3]Unless they happen to update their absolute preferences in the opposite direction of policy change.

electorate may view the same change as being small.[4] These differing reactions to perceived changes are well-documented and studied in the literature (for example Bartels 2002; Bullock 2009; Bullock et al. 2015). The result of this is that partisan groups under-react to policy change from their own party and overreact to policy change from the other party.

Partisans whose party does not control the government may be more skeptical of policy change and rate policy changes as being larger than partisans whose party does control the government. Put alternatively, partisans may give the government more leeway to change policy when it is controlled by their party. If this is the case, we will see greater policy responsiveness among out-partisans, since they view the magnitude of policy change as greater than that of in-partisans.

2.1.2 Explanation 2: Changes in Absolute Preferences

Because relative preferences contain information about absolute preferences *and* (belief about) policy, it is possible that even if partisans update their beliefs about policy (change) identically, they can still show differences across partisan lines if they change their absolute preferences (P^*) differently. We know that party greatly affects political preferences (Angus Campbell et al. 1960; Cohen 2003; Gerber, Huber, and Washington 2010; Colombo and Kriesi 2016).

In particular, we know that sometimes partisans update their preferences to be more in line with what their partisan elites are signaling (Cohen 2003; Ray 2003; Lenz 2009; Brader and Tucker 2012). In other words, partisans in the electorate cue take from their party elite. Furthermore, the literature on partisan motivated reasoning suggests that partisans may support (or oppose) policies that they would otherwise oppose (or support) based on which party is offering the policy (Bolsen, Druckman, and Cook 2013). And, in fact, signals from the opposing party may in fact be more powerful than signals from partisans' own parties (Goren, Federico, and Kittilson 2009).

Given this, we might expect that individuals' responses to policy spending changes may

[4] Of course, there is a "correct" answer to the spending change, since we can measure this in dollar terms. However, reasonable people can still disagree over whether a given change is "small" or "large."

depend on their partisanship. If partisans are more likely to take their party's position as their own, then they should move their absolute preferences (P^*) to be more in line with the policies that their party is proposing. Conversely, out-partisans may be more responsive than they would be otherwise as they shift their absolute preferences away from what the other party is doing. To be clear, individuals receive (and most likely react to) cues from both parties as these parties either justify (if in power) or criticize (if in opposition) spending (Goren, Federico, and Kittilson 2009).

In the context of the model at hand, partisans could cue take from the direction of spending. If a Democrat-controlled government spends more on policy X, then Democrats in the electorate could adjust their preferred level of policy X up. At the same time, Republicans in the electorate may adjust their preferred level of spending on policy X down. If that is what happens, then Democrats would appear to behave less thermostatically than Republicans.

To see this, consider Equation 1. Relative preferences are a function of absolute preferences and policy. If both P^* (on the left side, as a constituent part of R) and P (on the right hand side) move in tandem from $t-1$ to t, then this will force β_1 towards zero, all else equal. In other words, if in-partisans move their absolute preferences in the same direction as policy change, we will find evidence of little or no thermostatic feedback. Conversely, should out-partisans move their absolute preferences in the opposite direction of policy change, then we should find evidence of greater thermostatic feedback.

2.1.3 Salience

It is important to note that we should not expect the magnitude of thermostatic feedback (β_1) to be identical across issues. Issue-specific features can have a significant impact on this process. We know that issue salience plays a role in this process (Soroka and Wlezien 2010). Issues that are not salient are much less likely to exhibit thermostatic behavior; the public simply isn't paying much attention to those issues. If the public does not know much about an issue, then there is little reason to suspect that partisans react differently from each other.

Of the issues analyzed here, foreign aid seems especially unlikely to exhibit thermostatic feedback. There is ample polling data noting that foreign aid is an area many Americans simply do not pay much attention to and have little understanding of how much the U.S. spends on foreign aid or how that changes over time. Thus, we should not expect to see thermostatic feedback in this policy area; spending changes should not produce changes in relative preferences. And while there are differences in the magnitude of feedback across issues, we may suspect that the magnitude varies across individuals as well.

2.1.4 Partisan feedback

If individuals' reactions to policy changes depend on whether or not their party is in control of government, as suggested above, we need to modify Equation 2 to account for this:

$$R_{ij} = \beta_0 + \beta_1 P_{ij} + \beta_2 I_{ij} + \beta_3 PI_{ij} + \beta W_{ij} + \varepsilon_{ij} \tag{3}$$

where the variables are the same as above. We have added a new term, however. I represents whether they are "in-partisans," and PI is the interaction of those two terms. Thus, for in-partisans, their responsiveness to policy change is governed by $\beta_1+\beta_3$. Responsiveness of out-partisans, on the other hand, is simply β_1. Recall that if individuals behave thermostatically, then β_1 will be negative. Therefore, if in-partisans react less strongly to policy change, β_3 will be positive (making the overall effect of P on R less negative).

3 Data & Measurement

In order to estimate Equation 2 and Equation 3, we need data on political opinions, partisanship, sociodemographic information, and spending on public policy. For opinion, partisanship, and sociodemocraphic information, I use data from the 1973–2014 General Social Survey, run by NORC at the University of Chicago. The survey aims to collect a nationally representative sample of U.S. adults and ran almost yearly from 1973–1994 then biannually afterward. Dropping independents from the sample means that the analysis relies on 46,115 observations.[5]

For spending data, I use the *Historical Tables* from the Office of Management and Budget. The OMB reports spending data according to function and subfunction. So, for example, under function "350 — Agriculture" we can find subfunctions "351 — Farm income stabilization" and "352 — Agriculture research and services." I follow the methods employed by Soroka and Wlezien (2010, page 184) in order to aggregate spending data to the policy areas that the GSS asks about. Areas common to both the GSS and *Historical Tables* include welfare, big cities, health, the environment, education, foreign aid, crime, and defense. I then adjust the spending amounts for inflation. All dollar amounts are in tens of billions of 2000 dollars.

The W term represents a host of variables meant to capture change in P^*. We can think about these in terms of individual-level variables meant to capture variation across individuals and year-level variables meant to capture variation across years. In this analysis, individual-level variables included are sex, race, education, region, and which question version the respondent received.[6] For defense, two other variables are added. One captures how the respondent feels towards Russia, which has been found in previous work to be a good proxy for the "hotness" of the Cold War (and thus related to spending preferences for defense) (Wlezien 1995).[7] The other is an indicator variable that is a 1 between 2001 and 2010 and a

[5]Following Keith et al. (1992), I code partisan "leaners" as partisans, only dropping "true" independents. A separate analysis on independents shows that independents do not react differently to policy change under a Republican or a Democrat, with the exception of defense spending, where they appear to respond more strongly to spending by Republicans.

[6]For the relative preference questions, the GSS embeds a question wording experiment. Half of respondents receive one version of the question and half another. For example, half of respondents are asked about whether we spend too little, too much, or about the right amount on "the military, armaments, and defense," whereas the other half are asked about "national defense." Some of these question wordings (like defense) seem to make little difference. Others, (such as asking about "welfare" versus "assistance to the poor") make quite a large difference. In order to include as many respondents as possible, I merge responses to both the question wordings together and include an indicator variable for which wording the respondent received, which allows the mean of the dependent variable to vary based on question wording.

[7]The GSS stopped asking this question after 1994. We set the value of this variable to the mean in 1994 for all observations afterward.

0 otherwise.[8] This should capture some of the increase in absolute preferences for defense spending associated with the attacks on September 11th. Year-level variables included in the model are a counter, which allows for a linear trend for increasing (or decreasing) preferences over time.[9]

Measuring I is tricky. In the context of the United States, it is rarely the case that one party "controls" government. The separation of elections of the House, Senate, and Presidency means that one party usually controls at least one of those three policymaking institutions. For this article, I measure I as an indicator variable for whether or not a person is of the same party as the president. In U.S. politics, the president (and their party) tend to get credit for when the country is doing well and blamed when it is not, even if they have little to do with it (see, for example MacKuen, Erikson, and Stimson 1992). Hence, party control of the presidency is a good measurement for I. Let us now turn to the analysis.

4 Analysis

Before adding partisanship to the thermostatic model, let us first check to see how it works at the individual level. Recall from above that salient issues are more likely to display thermostatic feedback than nonsalient issues (see also Soroka and Wlezien 2010). Measuring salience is notoriously difficult. In the public opinion literature, the canonical way to measure salience is with the "most important problem" question regularly asked by Gallup. However, this question contains information about the extent to which an issue is important *and* is a problem (Wlezien 2005). It can, however, give us an idea of the salience of each issue area. Unfortunately, "foreign aid" is not included in this data.[10]

Figure 1 plots the average number of respondents who list each issue as the most important

[8]Coding it as a 1 for all years post 2001 instead of reverting back to a 0 does not change the results.

[9]An additional analysis was run including the square of the counter, which would allow for the effect of time to curve. This variable was found to be estimated very close to zero for all models. It also did not affect the substantive interpretation of the results; in the interest of parsimony, it was excluded.

[10]Data come from the U.S. branch of the Comparative Agendas Project, which hosts data concerning the most important problem. The Comparative Agenda Project aggregates the data and recodes it to use their major topic issue scheme.

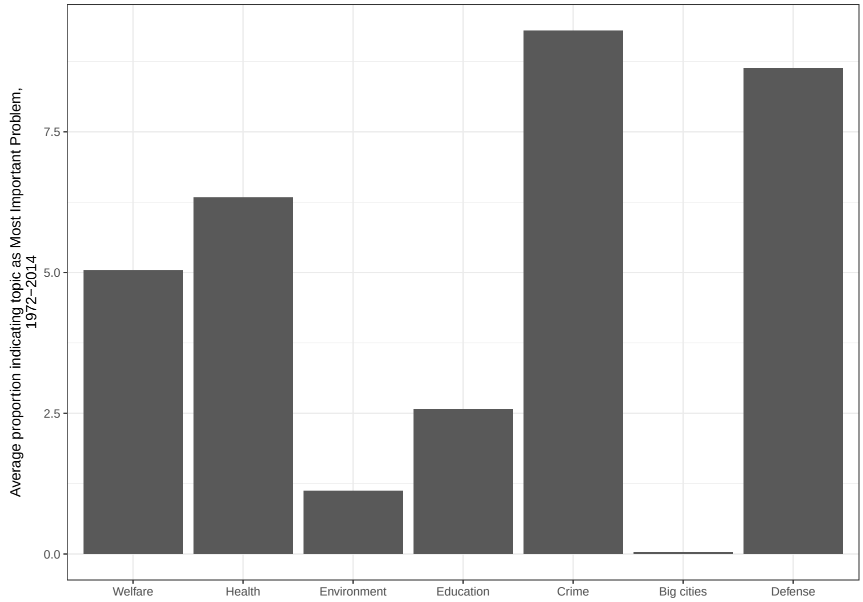

Figure 1: Issue salience. Bar heights represent the percent of respondents listing each issue at the "most important problem," averaged across years.

problem across years. Of the seven issue areas for which we have data, four — welfare, health, crime, and defense — stand out as highly salient.[11] Three other areas — big cities, the environment, and education — are much less salient. It seems reasonable to assume that foreign aid is a very low salience issue. Most Americans do not pay attention to this issue area and know relatively little about it (for one survey among many, see Kaiser 2013).

Let us turn to assessing the thermostatic model at the individual level. First, we estimate Equation 2, where the estimated sign of β_1 tells us about policy feedback. If negative, then the thermostatic model works as normal. As the dependent variable is trichotomous with ordered outcomes ("too little," "about right," "too much"), I use an ordered probit model to estimate Equation 2 separately for each of the eight policy areas. I estimate the regressions in a Bayesian framework using improper uniform priors on the unknown parameters.[12] Point

[11]If we use measures of media issue attention by looking at the proportion of New York Times articles covering each topic, we obtain a similar graph. One important difference is that welfare is covered much less, so it appears less salient. Given the rhetoric surrounding welfare and the relatively noticeable role it plays in campaigns and political speeches (for example, the "welfare queen" rhetoric), it seems likely that welfare is a high-salience issue, at least in this context.

[12]Bayesian estimation makes the calculation of statistical uncertainty associated with the predicted probability much easier (see Ai and Norton 2003, for a discussion of the difficulty of calculating the effects of interaction terms in nonlinear models). The samplers were run for 10,000 iterations, the first 1,000 of

estimates for the coefficients are reported in Appendix A.

Because the meaning of coefficients from an ordered probit analysis can be difficult to interpret, I focus on reporting predicted probabilities instead. It is important to note, however, that the mean of the posterior estimate for the coefficient associated with spending is negative in all cases, suggesting that the logic of the thermostatic model works quite well at the individual level.

Let us now turn to the analysis. Figure 2 plots the predicted probability of saying "too little" for each of the policy areas.[13] The horizontal axis is levels of spending on a policy in tens of billions of 2000 dollars and the predicted probability is along the vertical axis. The lines represent posterior means and the shaded areas represent 95 percent highest posterior densities. The horizontal axis ranges from the minimum observed value in each spending domain to the maximum observed value.

One feature of the data that these predicted probabilities highlight is the lopsided nature of respondents' answers to some of the questions. The *levels* of some predicted probabilities are always quite high or quite low. For example, the predicted probability of saying "too little" when asked about spending on several issues — crime, education, the environment, and health — is always quite high. Conversely, the predicted probability of saying "too little" is being spent on foreign aid is always quite low. This is a feature of the data; it is simply the case that most people say that they prefer more or less spending on certain policies. So although the predicted probabilities in Figure 2 for saying "too little" is being spent on welfare are always quite low, they would be much higher if instead we presented the predicted probability of saying "too little" is being spent on "assistance to the poor," the alternative

which were discarded as burn-in. Analyses to ensure that the samplers were well-behaved are available in Appendix C.

[13] The predicted probability of saying "too much" or "about right" is omitted from this figure for ease of interpretation. Predicted probabilities for all three answer choices are included in Figure 6 in Appendix B. In order to obtain predicted probabilities from the model, we need to specify values for all the variables included in the model. For the spending values (the horizontal axis), the smallest value is the minimum spending level observed and the largest value is the maximum observed spending value in each policy area. The other variables are set so that these predictions represent an individual who did not answer the "alternative" question wording, and is a white female with a high school education from the East North Central region of the country in 2014. For defense, the value for "Russia" was set at its observed mean.

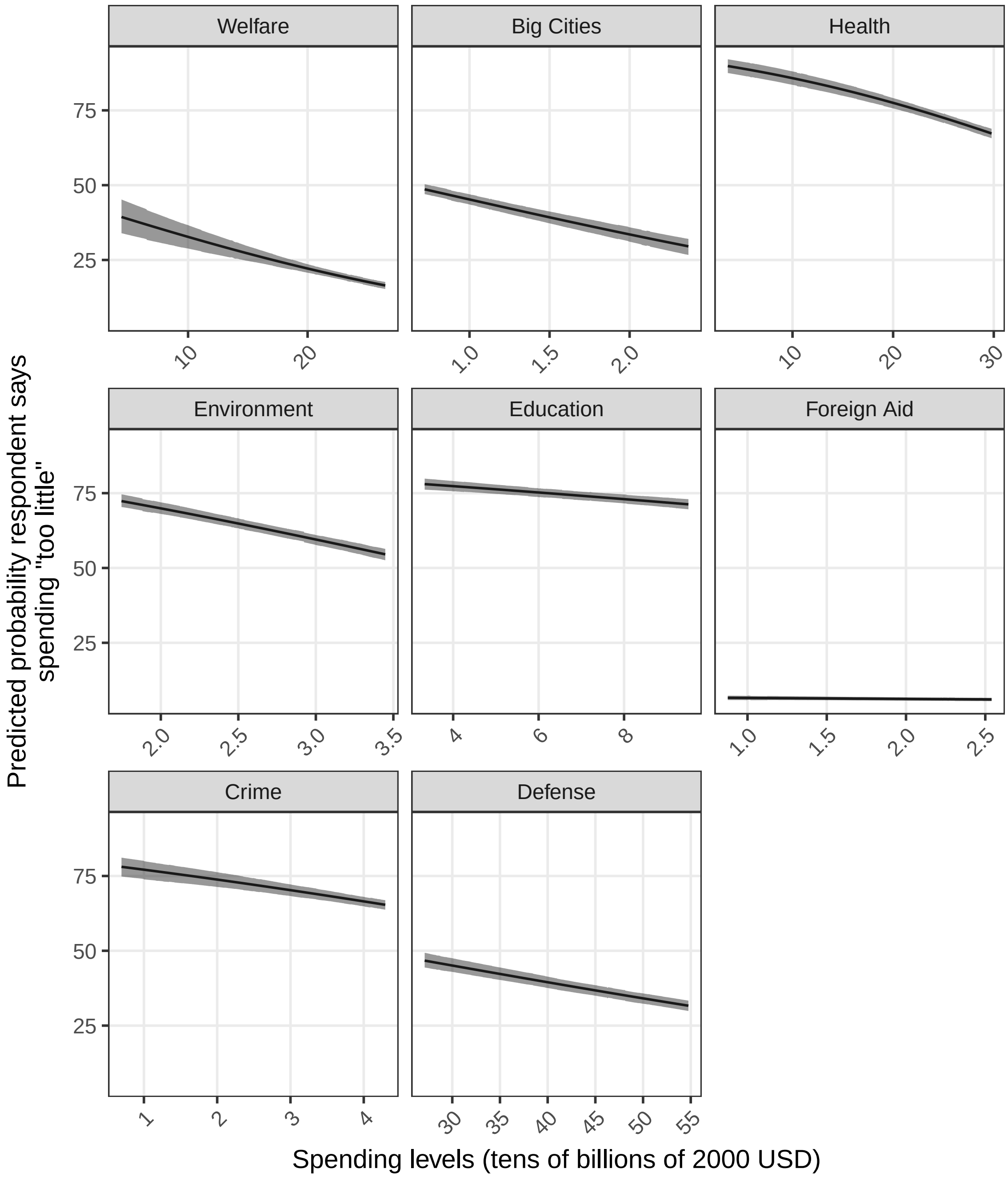

Figure 2: Policy feedback at the individual level. As the spending level on a policy increases, the predicted probability of preferring more spending decreases. Each panel presents predicted probabilities from Equation 2.

wording for that question.

In every issue area, the trend of the predicted probabilities for saying "too little" is negative. This indicates that the predicted probability on every issue for saying "too little" decreases as spending increases, which is what the thermostatic model predicts.

That said, there are clearly different patterns depending on the issue. For some issues, the trend of the predicted probabilities is much steeper than others. Foreign aid, for example, shows almost no thermostatic feedback. On the other hand, higher-profile issues like welfare and defense exhibit relatively large differences depending on the spending level. These differences are important; they suggest that people are more responsive to spending changes in some domains than others. In particular, people are basically unresponsive to spending changes in foreign aid, and only modestly responsive to spending changes in education, two low salience issues. There is relatively strong thermostatic feedback in the remaining domains: big cities, crime, defense, the environment, health, and welfare.

Clearly the thermostatic model works well at the individual level across a wide range of issues. As spending goes up, the predicted probability of saying "too little" goes down and the predicted probability of saying "too much" goes up. However, as discussed above, there are compelling reasons to think that not all people respond to spending changes the same. In particular, we may be interested in how partisanship affects the thermostatic model.

Of course, given what we know about the relatively low levels of political engagement in the public, it seems likely that individuals err when they update P. In other words, they may overreact to some policy changes and underreact to others.

If this overreaction or underreaction is systematic in a segment of the population, then this would produce differences in how they react to policy changes. One hypothesis of this sort, for example, would be that individuals on the low end of the political engagement scale are less likely to update their belief about where policy is given policy change than highly engaged people. We may also be interested in whether (and how) partisanship impacts this relationship.

4.1 Partisan Differences

We know that thermostatic behavior can vary depending on issue specific characteristics like salience. We might expect to see greater differences in thermostatic behavior on salient issues where partisans have larger disagreements. On some issues, there are smaller disagreements across party lines. On other issues, there is much larger disagreement. Areas with larger disagreements across partisan lines seem to be more likely to display differences in thermostatic feedback across partisanship, as it is these areas where partisans think less like each other.

Let us investigate the degree to which partisans agree or disagree with each other. In order to look at partisan disagreement, we can calculate net support for additional spending by each party (for additional analysis of this measure, see Wlezien 1995; Soroka and Wlezien 2010). To do this, we simply take the proportion of people who want more spending and subtract the proportion of people who indicate they prefer less spending. So the score for one group can range between -100 (if everyone prefers less spending) and 100 (if everyone prefers more spending).[14] Figure 3 plots net support by partisanship over time. Democrats are represented by the solid blue line and Republican net support by the dashed red line.

Several things are apparent from this figure. First is that there is clear partisan disagreement on many issues; the two lines are only rarely at the same point at the same time for any issue, with the exception of crime. Second is that Republican net support is lower than Democrats on average in all issue areas save spending on defense. Third is that the two groups do trend together. When net support among Republicans rises (or falls), net support among Democrats tends to rise (or fall) as well. Finally, although it is difficult to tell with any degree of precision just by looking at Figure 3, we might suspect that in recent years the gap in net support between the two parties has increased for many of the policies at hand.

However, if we are interested in how much partisans agree or disagree on issues, we can construct a simpler measure by taking the difference of net support between the two groups.

[14] Statistics in this section combine data from two question wordings so as to be consistent with the rest of the paper. See footnote 6 for more details.

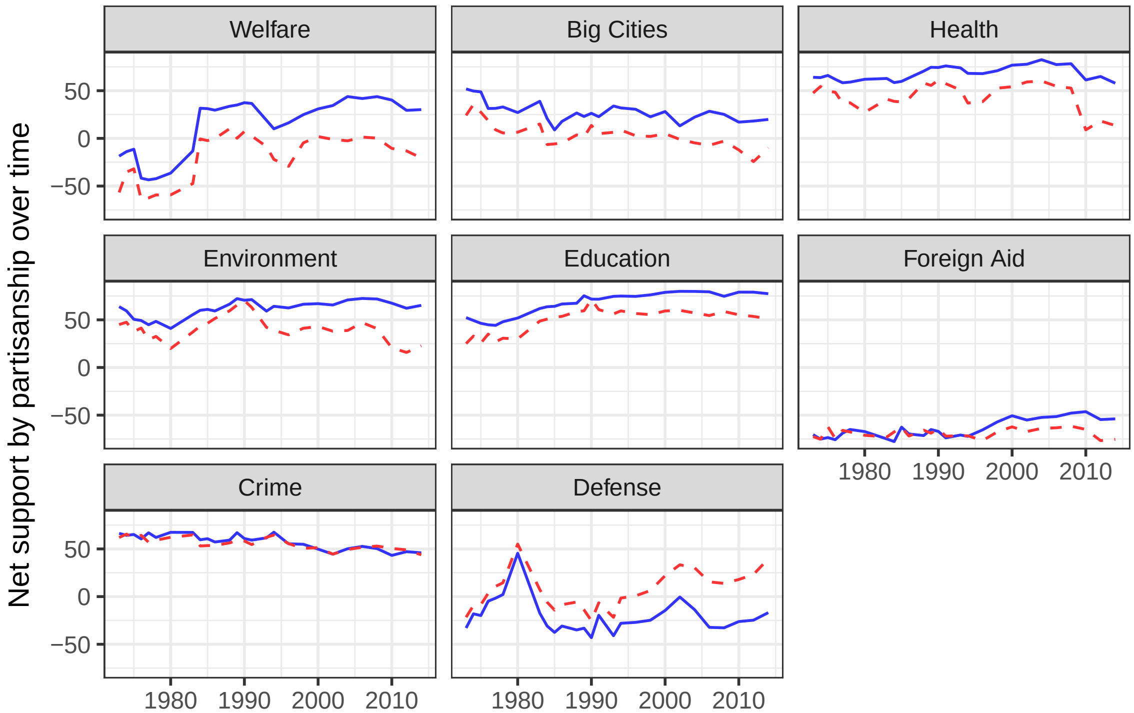

Figure 3: Net support by partisanship and year across issues. Net support is calculated by taking the percent of each group who prefer more spending minus the percent who prefer less. Democratic net support is represented by the solid blue line and Republican net support is represented by the dashed red line.

That is, we subtract the net support of Republicans from the net support of Democrats and average across years. Figure 4 presents just this. The difference in net support by partisanship is positive in nearly every policy area, indicating that on average, Democrats are more supportive of increased spending than Republicans, with the exception of defense.

The magnitude of this difference in net support varies quite a lot, however. Support for additional spending on foreign aid and crime appears to be relatively similar across partisan lines. This means that the average Democrat is only slightly more in favor of increased spending than the average Republican. Other issue areas exhibit much larger differences; in particular, welfare and defense exhibit the largest differences by party, while health, big cities, and the environment exhibit smaller differences.

Recall that theoretically, we expect to see partisan feedback on salient issues with relatively large disagreement across partisan lines. Table 1 places each issue in a two by two table

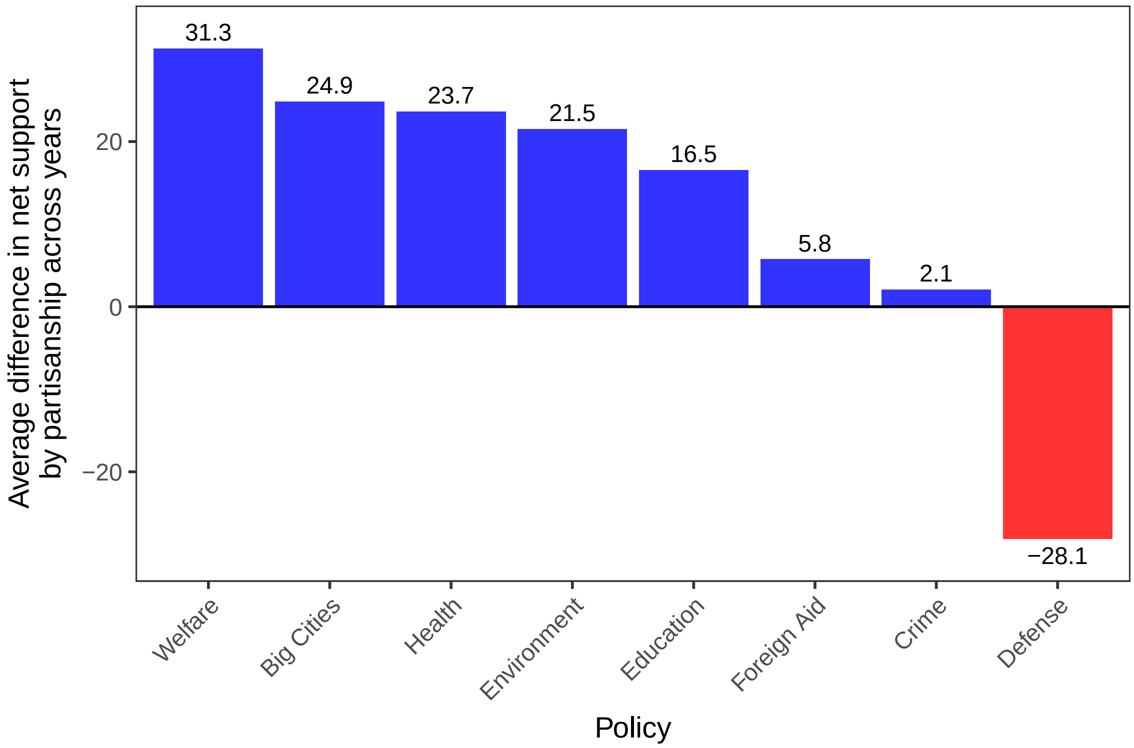

Figure 4: Differences in net support by partisanship. Democrat net support is greater than Republican net support on all policy areas except defense. The magnitude of the difference, however, varies dramatically.

depending on whether the issue is high salience or low salience and whether we see low or high partisan disagreement. Thus, crime, for example, is a high-salience issue on which we see relatively low disagreement across partisan lines. If partisans react differently to policy change on high-salience, high-disagreement issues, then we should expect to see differences in thermostatic responsiveness in welfare, health, and defense. Let us now see whether that is the case.

	Low salience	High salience
Low disagreement	Foreign Aid	Crime
High disagreement	Education, Big Cities, Environment	Welfare, Health, Defense

Table 1: Issue salience and partisan disagreement. This table places issues by low-high salience and low-high partisan disagreement. See Figure 1 and Figure 4 for more information.

4.2 Heterogeneity in Opinion Responsiveness

In order to estimate differences in partisan responsiveness, we will estimate Equation 3. Out partisan responsiveness is represented by β_1 and in-partisan responsiveness is governed by $\beta_1 + \beta_3$. The hypothesis is that for high-salience issue areas with disagreement across partisan lines (welfare, health, and defense; see Figure 1 and Figure 4), β_3 will be positive, indicating that in-partisans react less strongly to policy changes than out partisans. Conversely, for low-salience areas, or where partisans do not disagree much (big cities, foreign aid, education, the environment, and crime), β_3 should be near zero, indicating that out-partisans and in-partisans react in much the same way to policy change (which could include no reaction at all).

As above, I estimate the model in a Bayesian context separately for each policy area.[15] Substantive effects from ordered probit models are difficult to see looking just at the coefficients, and with interaction terms in the model, the task becomes much more difficult (Ai and Norton 2003). Therefore, as above, I focus on reporting predicted probabilities.[16]

Figure 5 presents predicted probabilities from the model.[17] The key difference between here and Figure 2 is that we separate thermostatic responsiveness by partisanship. In-partisans — those whose party controls government — are represented by the solid blue-green line whereas out-partisans are the dashed orange line. What can we learn from taking into account partisan status?

With only a few exceptions, the trend of all of the predicted probabilities representing people indicating they think we're spending "too little" have a negative slope. In other words, as spending on most policies increases, the probability of individuals indicating that they prefer more spending decreases, as the thermostatic model predicts. This is the case whether we take partisanship into account or not for most issue areas. There are some areas, however,

[15]Sampler diagnostics are reported in Appendix C.

[16]Estimates of posterior means of the coefficients are available in Appendix A, Table 3.

[17]As before, predicted probabilities for "too much" and "about right" are omitted for ease of interpretation. They are reported in Figure 7 in Appendix B. Values for the other variables as well as the scale of the axes are all the same as presented in Figure 2, see footnote 13.

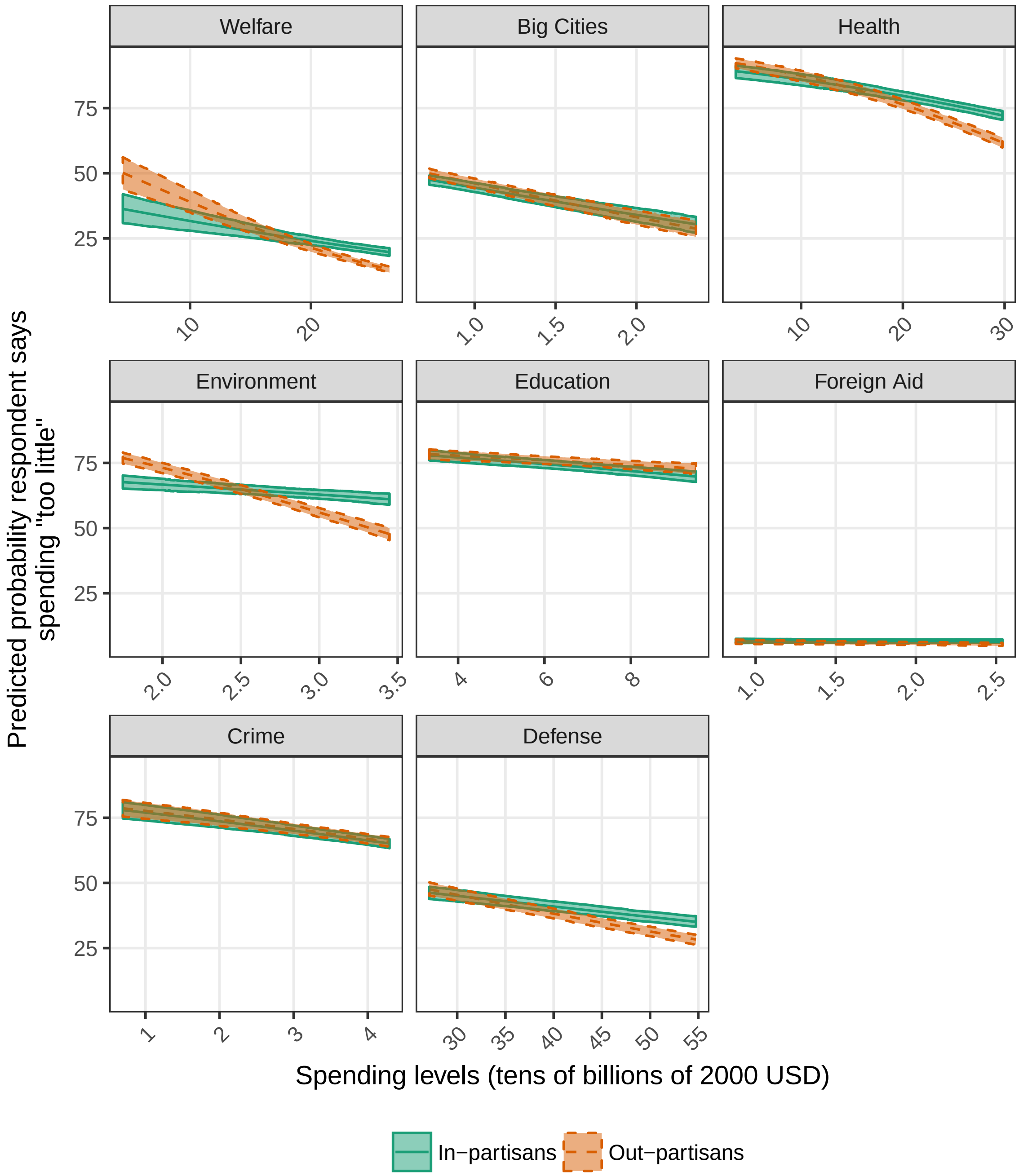

Figure 5: Partisanship and policy feedback. Each panel presents predicted probabilities from Equation 3. As the spending level on a policy increases, the predicted probability of each answer option changes conditional on partisanship.

where partisanship into account makes a great deal of difference.

Above, I argued that we should expect to see differences in thermostatic feedback across partisan groups on high-salience issues with relatively large disagreement across partisan lines (welfare, health, and defense). Specifically, the trend for the predicted probabilities should be flatter for in-partisans than out-partisans among those issues. If this is the case, then we can conclude that in-partisans behave less thermostatically than out-partisans. These three issue ares do in fact display differences in thermostatic responsiveness. I also unexpectedly find that partisans react differently to spending on the environment. In none of the eight policy areas do the results go in the opposite direction of expectations.

In these four policy areas, (defense, the environment, health, and welfare) in-partisans are *less* responsive to spending than out-partisans — the trend of the predicted probabilities is flatter. This means that in-partisans are less likely to change their stated relative preferences for more (or less) spending as spending changes.

These four areas also all exhibit large disagreement across partisan lines (see Figure 4). And, although spending on the environment has not historically been a highly divisive issue, in recent years it has become much more divisive (see Figure 3), which may account for the differences we see in Figure 5. Of these four areas, three are highly salient. Defense, health, and welfare rank highly among "most important problem" measures (see Figure 1).

There do not appear to be large differences in thermostatic behavior across partisan lines on foreign aid, big cities, crime, and education. Spending on foreign aid and crime exhibits very little disagreement by partisanship (again, see Figure 4), and only slight disagreement across partisan lines exists on education. Estimates from the model predict that there are not substantive differences in thermostatic feedback with regard to spending on big cities, even though there exists relatively large disagreement across partisan lines in this area (see Figure 4). This is likely because big cities is not a salient issue area.

Taken together, the weight of the evidence presented here suggests that partisanship can and oftentimes does play an important role in the thermostatic process. It appears to play the largest role on the most important issues — salient issues with relatively large disagreements across partisan lines. Differences in thermostatic behavior are smaller among issues where the two sides tend to agree, or if the issue area is not very salient.

5 Discussion

This paper began by considering a tension in the existing literature. Previous research shows that the public reacts to policy changes (for examples, Wlezien 1995; Soroka and Wlezien 2010) and that public opinion among various subgroups changes roughly in parallel over time (Page and Shapiro 1992). At the same time, research focusing on how partisans update and maintain their preferences suggests that we should see differences across partisan groups (see discussion in subsection 2.1). However, if partisans really do differ so drastically in how they interpret information, why do we see such parallelism in their opinions over time?

Analysis reveals that there are differences in how people update their relative opinion for more or less policy in response to policy changes based on partisanship on salient issues with disagreement across partisan lines. Specifically, partisans whose party controls the government are less responsive to policy changes in those areas than out-partisans. Theoretically, reasons to expect these differences based on differences in monitoring, accountability, and cue taking. There could, of course, be other mechanisms driving the observed relationship. Pinning down the exact causal mechanisms is a task for future research in this area.

Of the eight issue areas analyzed, we expected to find differences in thermostatic feedback in the three high-salience, high-disagreement areas (welfare, health, and defense; see Table 1). In fact, there are substantive differences in thermostatic feedback by partisanship in four issue areas — defense, the environment, health, and welfare (see Figure 5 and accompanying discussion). In these four areas, in-partisans are *less* responsive to changes in spending than out-partisans. None of the eight policy areas analyzed have results in the opposite direction.

These results suggest that there is an important role for partisanship in how people change their opinions in response to policy changes. For some policies, it takes larger changes in spending to produce changes in opinion among partisans whose party controls government. On the other hand, partisans' thermostatic behavior is stronger when the other party is in control; a moderate change in spending can produce larger changes in opinion among out-partisans. These differences imply that we do not understand parallelisms in public opinion as well as we had thought. Shifts in public opinion across policy areas are at least sometimes conditional on partisan control of government. This has implications for the literature on public opinion. It suggests that we need to consider partisan control of government as an additional variable that can impact how partisans react to government policy.

Partisan feedback also matters for representation. Partisans apparently give their own party more leeway to change policy and less leeway to the other party, at on salient issues where they disagree with the other side. This suggests that parties may have a very hard time convincing members of the opposite side of their policy successes, especially in policy areas with large disagreements like defense and welfare. Now, in addition to attitudes such as political trust (Claassen and Ensley 2016), we now know that partisanship can shape responses to policy change.

This can have very real consequences for public opinion and other political outcomes. As others have already shown, higher levels of partisanship in the public decrease the effect of short-term shifts in policy on electoral outcomes (Kayser and Wlezien 2011; Ezrow, Tavits, and Homola 2014). The finding that partisans adjust their opinions differently in response to policy change supports these findings, as it implies that partisanship may weaken these policy-based democratic linkages. However, other policy areas such as spending on big cities or education may be easier to find common ground, as the party bases tend to react to policy change very similarly.

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A Parameter estimates

Interpretation of regression output for ordered probit models is notoriously difficult. For that reason, I focus on predicted probabilities in the paper. I report here the posterior means and standard deviations of the regression coefficients. Table 2 reports the results from estimating Equation 2 and Table 3 reports the results from estimating Equation 3.

Table 2: Regression output summary for models estimated from Equation 2

Parameter	Statistic	City	Crime	Defense	Education	Environment	Foreign Aid	Health	Welfare
Spending	Mean	-0.305	-0.106	-0.014	-0.034	-0.281	-0.026	-0.032	-0.032
	(SD)	(0.02)	(0.014)	(0.001)	(0.006)	(0.021)	(0.015)	(0.003)	(0.004)
Russia	Mean			0.046					
	SD			0.004					
Intercept	Mean	1.527	1.549	0.415	0.991	1.871	-0.614	1.268	0.171
	(SD)	(0.044)	(0.033)	(0.047)	(0.037)	(0.057)	(0.041)	(0.033)	(0.033)
Alt wording	Mean	-0.756	-0.225	-0.028	0.13	0.056	-0.143	-0.076	1.209
	(SD)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
Counter	Mean	-0.007	0.003	0.017	0.015	0.003	0.009	0.023	0.021
	(SD)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
HS Educaiton	Mean	0.067	0.111	-0.1	0.258	0.254	-0.136	0.084	-0.202
	(SD)	(0.016)	(0.017)	(0.018)	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)
Over HS Edu	Mean	0.175	-0.01	-0.365	0.362	0.372	0.128	0.008	-0.193
	(SD)	(0.018)	(0.018)	(0.02)	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)
Female	Mean	0.139	0.18	0.005	0.136	0.078	0.058	0.176	0.076
	(SD)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)
Cutpoint	Mean	1.077	1.208	1.2	1.096	1.071	1.022	1.006	0.917

Table 2: *(continued)*

Parameter	Statistic	City	Crime	Defense	Education	Environment	Foreign Aid	Health	Welfare
	(SD)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)
post911	Mean			0.139					
	SD			0.016					
Black	Mean	0.509	0.15	-0.295	0.437	0.219	0.198	0.428	0.749
	(SD)	(0.018)	(0.019)	(0.02)	(0.021)	(0.019)	(0.019)	(0.02)	(0.018)
Hispanic	Mean	0.204	-0.055	-0.361	0.037	0.119	0.4	-0.021	0.271
	(SD)	(0.029)	(0.029)	(0.029)	(0.031)	(0.03)	(0.029)	(0.029)	(0.028)
Middle Atlantic	Mean	-0.045	0.045	0.028	0.012	-0.064	-0.095	0.039	-0.12
	(SD)	(0.03)	(0.031)	(0.034)	(0.032)	(0.033)	(0.034)	(0.033)	(0.032)
E. Nor. Central	Mean	-0.154	0.08	0.102	-0.037	-0.18	-0.142	-0.12	-0.141
	(SD)	(0.03)	(0.031)	(0.032)	(0.031)	(0.032)	(0.033)	(0.032)	(0.03)
W. Nor. Central	Mean	-0.22	0.017	0.087	-0.031	-0.207	-0.117	-0.169	-0.15
	(SD)	(0.035)	(0.035)	(0.037)	(0.035)	(0.035)	(0.038)	(0.036)	(0.035)
South Atlantic	Mean	-0.314	0.131	0.28	0.048	-0.199	-0.078	-0.101	-0.184
	(SD)	(0.03)	(0.03)	(0.033)	(0.032)	(0.032)	(0.033)	(0.031)	(0.031)
E. Sou. Central	Mean	-0.417	0.179	0.321	0.08	-0.306	-0.143	-0.126	-0.198
	(SD)	(0.036)	(0.037)	(0.039)	(0.037)	(0.036)	(0.039)	(0.037)	(0.036)
W. Sou. Central	Mean	-0.318	0.132	0.307	-0.008	-0.267	-0.112	-0.187	-0.195

Table 2: *(continued)*

Parameter	Statistic	City	Crime	Defense	Education	Environment	Foreign Aid	Health	Welfare
	(SD)	(0.032)	(0.033)	(0.036)	(0.035)	(0.035)	(0.036)	(0.034)	(0.033)
Mountain	Mean	-0.265	-0.064	0.118	0.039	-0.28	-0.112	-0.17	-0.104
	(SD)	(0.035)	(0.036)	(0.038)	(0.038)	(0.037)	(0.038)	(0.037)	(0.035)
Pacific	Mean	-0.119	0.034	-0.013	0.041	-0.199	-0.036	-0.078	-0.114
	(SD)	(0.031)	(0.032)	(0.034)	(0.032)	(0.034)	(0.034)	(0.033)	(0.031)

Table 3: Regression output summary for interactive models

Parameter	Statistic	City	Crime	Defense	Education	Environment	Foreign Aid	Health	Welfare
Spending	Mean	-0.339	-0.108	-0.019	-0.029	-0.466	-0.050	-0.043	-0.051
	(SD)	(0.026)	(0.015)	(0.001)	(0.007)	(0.027)	(0.021)	(0.003)	(0.004)
In partisan	Mean	-0.108	-0.024	-0.252	0.025	-0.911	-0.018	-0.249	-0.481
	(SD)	(0.034)	(0.026)	(0.061)	(0.040)	(0.089)	(0.052)	(0.023)	(0.029)
Interaction	Mean	0.066	0.002	0.008	-0.012	0.363	0.048	0.018	0.028
	(SD)	(0.031)	(0.010)	(0.002)	(0.008)	(0.035)	(0.029)	(0.002)	(0.002)
Russia	Mean			0.046					
	SD			0.004					
Intercept	Mean	1.579	1.556	0.548	0.978	2.322	-0.598	1.373	0.392
	(SD)	(0.048)	(0.034)	(0.057)	(0.042)	(0.070)	(0.049)	(0.035)	(0.035)
Alt wording	Mean	-0.756	-0.226	-0.026	0.130	0.058	-0.143	-0.077	1.214
	(SD)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)
Counter	Mean	-0.007	0.003	0.017	0.015	0.003	0.008	0.025	0.023
	(SD)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
HS Educaiton	Mean	0.068	0.112	-0.100	0.258	0.261	-0.138	0.093	-0.189
	(SD)	(0.016)	(0.016)	(0.018)	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)
Over HS Edu	Mean	0.176	-0.009	-0.367	0.362	0.381	0.125	0.017	-0.180

Table 3: *(continued)*

Parameter	Statistic	City	Crime	Defense	Education	Environment	Foreign Aid	Health	Welfare
	(SD)	(0.018)	(0.018)	(0.020)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)
Female	Mean	0.139	0.181	0.005	0.135	0.075	0.057	0.175	0.074
	(SD)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)
Cutpoint	Mean	1.078	1.208	1.202	1.096	1.072	1.023	1.010	0.922
	(SD)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.010)	(0.009)	(0.007)
post911	Mean			0.149					
	SD			0.016					
Black	Mean	0.508	0.148	-0.293	0.436	0.206	0.201	0.410	0.724
	(SD)	(0.018)	(0.018)	(0.019)	(0.020)	(0.018)	(0.019)	(0.020)	(0.018)
Hispanic	Mean	0.201	-0.056	-0.358	0.034	0.114	0.402	-0.030	0.263
	(SD)	(0.030)	(0.029)	(0.030)	(0.032)	(0.031)	(0.030)	(0.030)	(0.029)
Middle Atlantic	Mean	-0.044	0.047	0.029	0.013	-0.060	-0.093	0.046	-0.115
	(SD)	(0.031)	(0.031)	(0.034)	(0.033)	(0.032)	(0.033)	(0.033)	(0.031)
E. Nor. Central	Mean	-0.154	0.081	0.101	-0.036	-0.177	-0.141	-0.112	-0.135
	(SD)	(0.030)	(0.031)	(0.033)	(0.031)	(0.031)	(0.032)	(0.032)	(0.030)
W. Nor. Central	Mean	-0.220	0.017	0.087	-0.029	-0.203	-0.115	-0.159	-0.143
	(SD)	(0.034)	(0.035)	(0.037)	(0.036)	(0.035)	(0.037)	(0.036)	(0.033)
South Atlantic	Mean	-0.315	0.133	0.282	0.048	-0.195	-0.076	-0.091	-0.176

Table 3: *(continued)*

Parameter	Statistic	City	Crime	Defense	Education	Environment	Foreign Aid	Health	Welfare
	(SD)	(0.030)	(0.031)	(0.033)	(0.031)	(0.032)	(0.031)	(0.031)	(0.029)
E. Sou. Central	Mean	-0.417	0.179	0.320	0.081	-0.306	-0.142	-0.122	-0.194
	(SD)	(0.036)	(0.037)	(0.040)	(0.038)	(0.036)	(0.037)	(0.037)	(0.035)
W. Sou. Central	Mean	-0.317	0.133	0.308	-0.009	-0.266	-0.110	-0.182	-0.193
	(SD)	(0.033)	(0.034)	(0.036)	(0.035)	(0.035)	(0.035)	(0.034)	(0.033)
Mountain	Mean	-0.265	-0.063	0.118	0.041	-0.277	-0.113	-0.161	-0.097
	SD	0.036	0.035	0.039	0.038	0.037	0.038	0.037	0.035
Pacific	Mean	-0.119	0.036	-0.015	0.041	-0.200	-0.036	-0.074	-0.111
	SD	0.032	0.032	0.034	0.033	0.033	0.032	0.032	0.031

B Figure of all predicted probabilities

In the interest of space and for ease of comparison, I show a figure (Figure 5) in the text of only the predicted probabilities of saying "too little" or "too much." The model, however, also makes predictions for saying "about right," which I report here. Figure 6 reports the same predicted probabilities as Figure 2 including all three response options, and Figure 7 does the same for Figure 5.

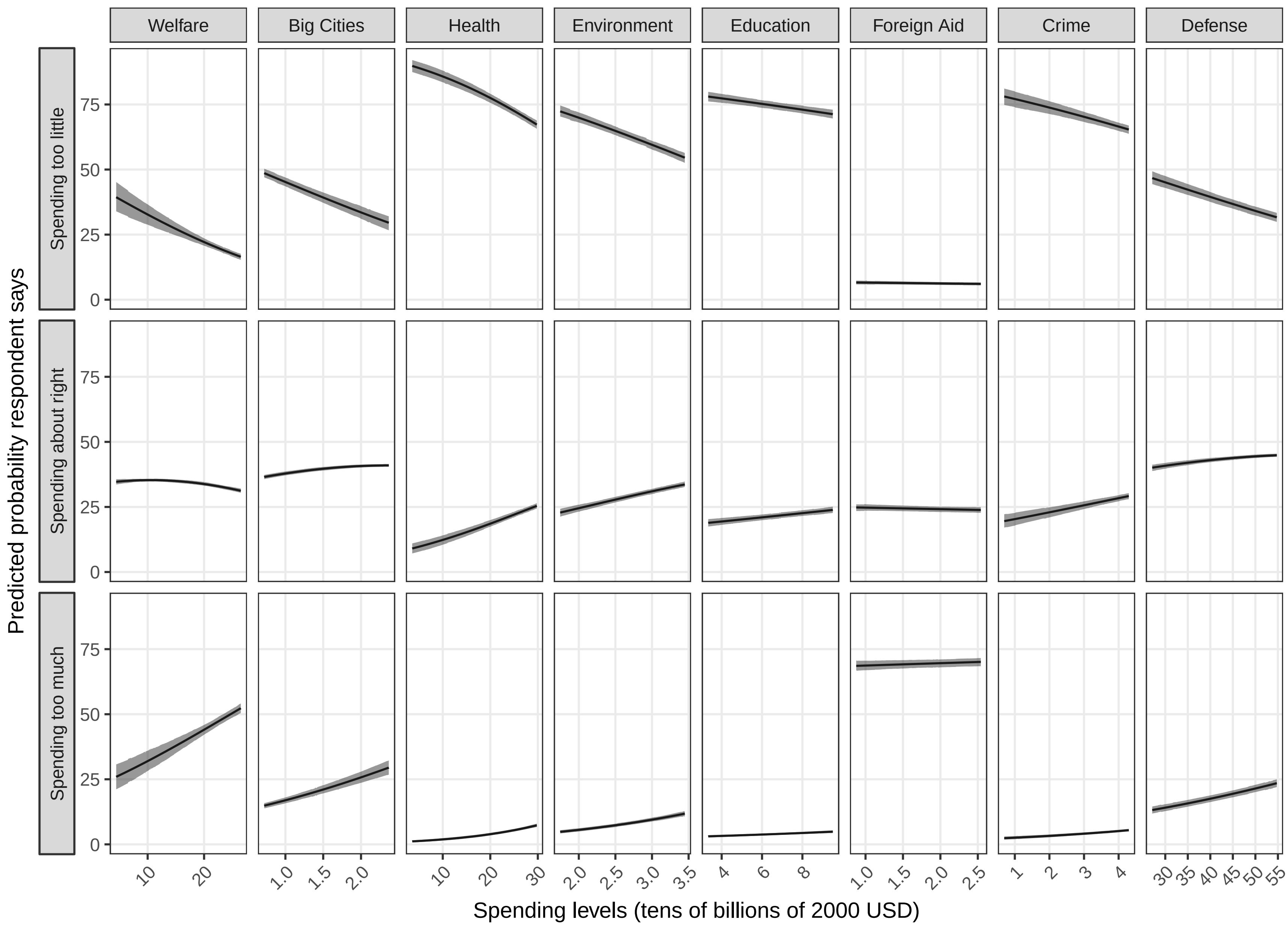

Figure 6: Predicted probabilities for all three answer options

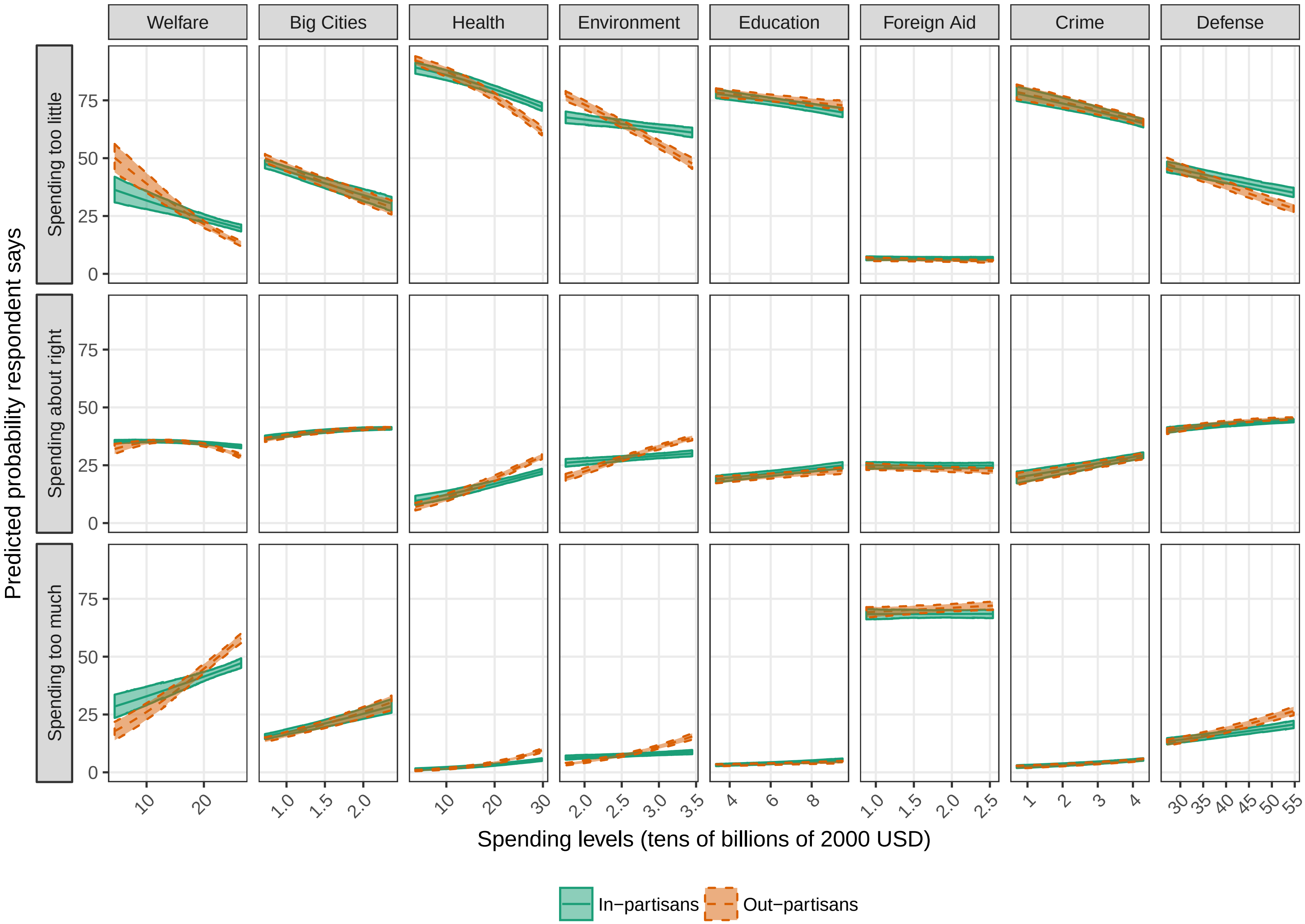

Figure 7: Predicted probabilities for all three answer options

C Convergence and autocorrelation checks

Inspections of output indicate that the samplers converged fairly quickly. I visually inspected some of the plots to see if there were any obvious indications of nonconvergence; there were none. I also ran geweke diagnostics on the output of the posterior simulation; for the noninteractive models estimated from Equation 2, only 9.88 percent of the parameters exhibited a z score of greater than 1.96 or less than -1.96. For the interactive models from Equation 3, 7.87 percent exhibited extreme z values; in expectation, five percent should.

I also visually inspected some of the autocorrelation function plots, which indicated some autocorrelation, which is to be expected. To allay fears of especially high autocorrelation, I used the `effectiveSize` function from the `coda` R package to calculate effective sample size. The mean effective sample size for the noninteractive models from Equation 2 is 1,941.93 and the minimum value is 536.77 . For the interactive models estimated from Equation 3, the mean effective sample size is 1,916.37 and the minimum is 559.14 .