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 issue areas with relatively large disagreement. This enhances our understanding of the interaction of partisan control of government and partisanship in the opinion-policy process. 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, 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, assuming that partisans react similarly to policy change 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), as well as other research that argues that we are seeing a steady increase in polarization in the American public (Abramowitz and Saunders 2008; Webster and Abramowitz 2017; though see Fiorina, Abrams, and Pope 2008; Fiorina and Abrams 2008).

In this paper, I identify three specific mechanisms that should all lead to partisan differences in policy feedback. Specifically, in comparison to supports of the non-incumbent party, supporters of the incumbent party (1) may not monitor government action as carefully, (2) may process information differently, and (3) 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. I refer to this difference as "partisan feedback."

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 issues. I then test these expectations using opinion and policy data from the United States from 1973 to 2014. I test a model of partisan feedback at the individual level across eight issue areas. Analysis reveals that (1) the thermostatic model works well at the individual level as well as the aggregate level (2) partisan feedback does occur (3) partisan feedback tends to occur in issue areas with relatively large disagreement across partisan lines.

2 Opinion Responsiveness

Changes in public policy can produce changes in public opinion. 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, not just political opinions (for a review of recent literature, see Andrea Campbell 2012).

The thermostatic model is one model of how public opinion can respond to changes in policy. It asserts that increases in policy are associated with decreases in demand for more of that policy. In other words, if government increases the amount of policy, then fewer people prefer further increases of that policy. This relationship has been studied extensively at the national level in the US (Wlezien 1995; Erikson, MacKuen, and Stimson 2002; Ellis and Faricy 2011), the U.S. state level (Pacheco 2013b), as well as cross-nationally (Soroka and Wlezien 2010).

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.

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

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 thermostatic model. 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).

If we are interested in the effect of policy change on relative preferences, we can model R as a function of P:

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

where R represents individual i's relative opinion (see Equation 1) for more or less spending on policy j. P represents the dollar amount spent and W represents a vector of variables meant to capture P^* since P^* is not directly observable.[1] Therefore, 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]The β term associated with W is a vector of coefficients.

3 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 through partisan "lenses" (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). We also know that partisanship has a causal influence on people's political preferencecs (Gerber, Huber, and Washington 2010).

What we already know about partisanship suggests that partisans should react differently to policy changes. However, previous work on thermostatic feedback finds only limited differences across partisan groups. Soroka and Wlezien (2010) find that Democrats, Independents, and Republicans (as well as partisan groups in Canada and the UK) respond very similarly to policy change. Ura and Ellis (2012) also find that partisan "mood" tends to move in parallel over time, but may be polarizing slightly in recent years. However, in this paper I argue that we should expect differences across partisan groups based not only on an individual's party, but also 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 likely mechanisms at work here. If we conceptualize relative preferences R as the difference between absolute preferences P^* and policy P (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.

3.1 Explanation 1: Changes in Policy

One possibility is that partisans see P — policy — differently from one another. 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 policy, 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 may monitor the government's actions more closely if the government is controlled by the opposite party. In other words, these groups are more attentive to changes in P. 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" (partisans whose party controls government) 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.[2] 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. If that is the case, we will observe in-partisans as behaving less thermostatically than out-partisans.

Differences in monitoring (in other words, the reception of information about policy change)

[2]Unless they happen to update their absolute preferences P^* in the opposite direction of 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 electorate may view the same change as being small.[3] These differing reactions to perceived changes are well-documented and studied in the literature (for example Bartels 2002; Bullock 2009; Bullock et al. 2015). Put alternatively, partisans may give the government more leeway to change policy when it is controlled by their party. If it is the case that one group views a policy change as larger in magnitude than another group, then the first will behave more thermostatically. 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.

3.2 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 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).

[3] 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."

Given this, we might expect that individuals' responses to policy spending changes may 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 may 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 our conceptualization of R, 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.

3.3 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 policy P and I. 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).

3.4 Considering Issue Characteristics

Of course, not all issues are the same. One issue-specific characteristics that may affect partisan feedback is the extent to which there is disagreement across partisan groups. We expect to see greater differences in thermostatic behavior when partisans have different opinions. On some issues, there are smaller disagreements across party lines. On other issues, there is much larger disagreement. Areas with large disagreement across partisan lines seem to be more likely to display partisan feedback, 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.[4] In order to look at partisan disagreement, we can calculate net support for additional spending by each party[5] 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).[6] Figure 1 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

[4]The data are described in more detail in section 4, below.

[5]For additional analysis of this measure, see Wlezien (1995) and Soroka and Wlezien (2010).

[6]Statistics in this section combine data from two question wordings so as to be consistent with the rest of the paper. See footnote 9 for more details.

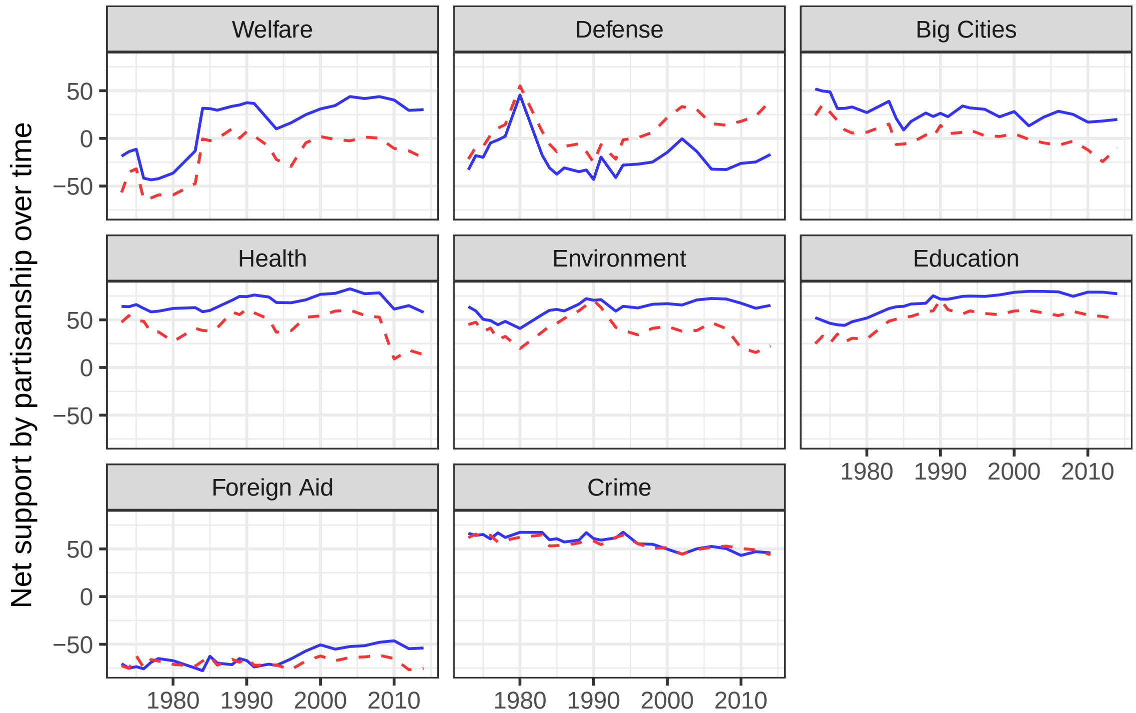

Figure 1: Net support by partisanship and year across issues. Net support is calculated by taking the percent of each group who prefer more spending minus the percent who prefer less. Democratic net support is represented by the solid blue line and Republican net support is represented by the dashed red line.

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 1, 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. This is in line with what Ura and Ellis (2012) find.

However, if we are interested in how much partisans agree or disagree on issues, we can construct a simpler measure by taking the absolute value of the difference of net support between the two groups. That is, we subtract the net support of Republicans from the net support of Democrats, take the absolute value, and average across years. Table 1 presents averages and extrema for this measure of partisan disagreement.

The magnitude of net support disagreement varies quite a bit across issues. Support for

Table 1: Disagreement and salience by issue area

Issue	Mean disagree	Min disagree	Max disagree	NYT salience	MIP salience
Welfare	32.87	17.03 (1978)	50.77 (2010)	0.55	5.03
Defense	26.33	8.26 (1976)	56.40 (2014)	3.48	8.63
Health	23.67	9.34 (1974)	52.36 (2010)	3.68	6.33
Big cities	23.63	12.65 (1990)	42.56 (2012)	1.63	0.03
Environment	20.53	0.29 (1990)	46.83 (2010)	1.60	1.12
Education	17.34	0.37 (1990)	27.22 (1973)	2.52	2.57
Foreign Aid	7.36	0.11 (1974)	22.05 (2012)	NA	NA
Crime	3.5	0.05 (2002)	9.90 (1977)	6.28	9.30

Measures of disagreement are constructed by taking the absolute value of the difference in net support by each year. In all issue areas except defense, Republican net support is lower on average than Democratic net support. The NYT measure is a measure of how often each issue appears on the front page. MIP measures the average percent of respondents listing each issue area as the most important problem. Data for the NYT and MIP are from the Policy Agendas Project.

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, defense, health, and big cities exhibit the largest differences by party, while the environment and education exhibit smaller, but still large differences. Thus, we might expect to find the largest differences in thermostatic feedback across partisan groups in these four issue areas. However, we must also take into account another issue-specific characteristic: salience.

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. There are at least two common ways of constructing a measure of salience. The most common measure relies on the so-called "most important problem" questions regularly asked by polling organizations, which contain information about both importance and the extent to which an issue area is a problem (Wlezien 2005). Another way of attempting to measure salience is through counting how often the issue area appears in newspapers like the New

York Times. Averages of both of these measures are shown in Table 1. Defense, health, crime, and education are among the most salient issues according to both measures. The MIP measure suggests that welfare should also be salient, though the NYT measure does not. Given that welfare is a common issue in campaign rhetoric, it seems like the MIP measure may be more reliable here. The environment and big cities are not rated as salient by either measure. Although neither asked about foreign aid, we know from previous work that we should not expect to observe thermostatic feedback in foreign aid because it is a low-salience issue where opinions are unrelated to policy status quo (Soroka and Wlezien 2010; Wlezien 2016).

Recall that theoretically, we expect to see partisan feedback on issues with relatively large disagreement across partisan lines. If partisans react differently to policy change on salient, high-disagreement issues, then we should expect to see differences in thermostatic responsiveness in welfare, defense, and health. We may also see partisan feedback in the environment and education, where there appears to be large disagreement, but it may not be as salient. We do not expect to see partisan feedback in big cities, foreign aid, or crime.[7]

4 Data & Measurement

In order to estimate 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.[8]

For spending data, I use the *Historical Tables* from the Office of Management and

[7]In foreign aid and crime, partisans largely agree. big cities and foreign aid are low-salience issues.

[8]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.

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. All dollar amounts are inflation-adjusted 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.[9] 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).[10] The second variable is an attempt to account for a potential increase in absolute preferences for defense spending associated with the attacks on September 11th. It is coded as an indicator variable that is a 1 between 2001 and 2010 and a 0 otherwise.[11] Year-level variables included in the model are a counter, which allows for a linear trend for increasing (or decreasing) absolute preferences over time.[12]

Measuring I is tricky because in the United States, it is rarely the case that one party

[9]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.

[10]The GSS stopped asking this question after 1994, so observations after 1994 are set to the mean level in 1994.

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

[12]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.

"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). Let us now turn to the analysis.

5 Analysis

In order to estimate differences in partisan responsiveness, we will estimate Equation 3. Responsiveness of out-partisans is represented by β_1 (the coefficient associated with P, since I is zero for out-partisans) and in-partisan responsiveness is governed by $\beta_1 + \beta_3$. The hypothesis is that for salient issue areas with disagreement across partisan lines (welfare, health, and defense), 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, 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). I do not have strong expectations either way about whether we should observe partisan feedback in education and the environment. These are medium disagreement issues that are also of middling salience.

As the dependent variable is trichotomous with ordered outcomes ("too little," "about right," "too much"), I use an ordered probit model to estimate Equation 3 separately for each of the eight policy areas. I estimate the regressions in a Bayesian framework using improper uniform priors on the unknown parameters.[13] Substantive effects from ordered probit models

[13]Bayesian estimation makes the calculation of statistical uncertainty associated with the predicted probability straightforward (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 which were discarded as burn-in. Analyses to ensure that the samplers were well-behaved are available in

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). For these reasons, I focus on interpreting predicted probabilities rather than the coefficients themselves. Point estimates for the coefficients are reported in Appendix B.

Figure 2 presents predicted probabilities from the model.[14] 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, 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 find that partisans react differently to spending on the environment. 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

Appendix D.

[14]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 4 in Appendix C. 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.

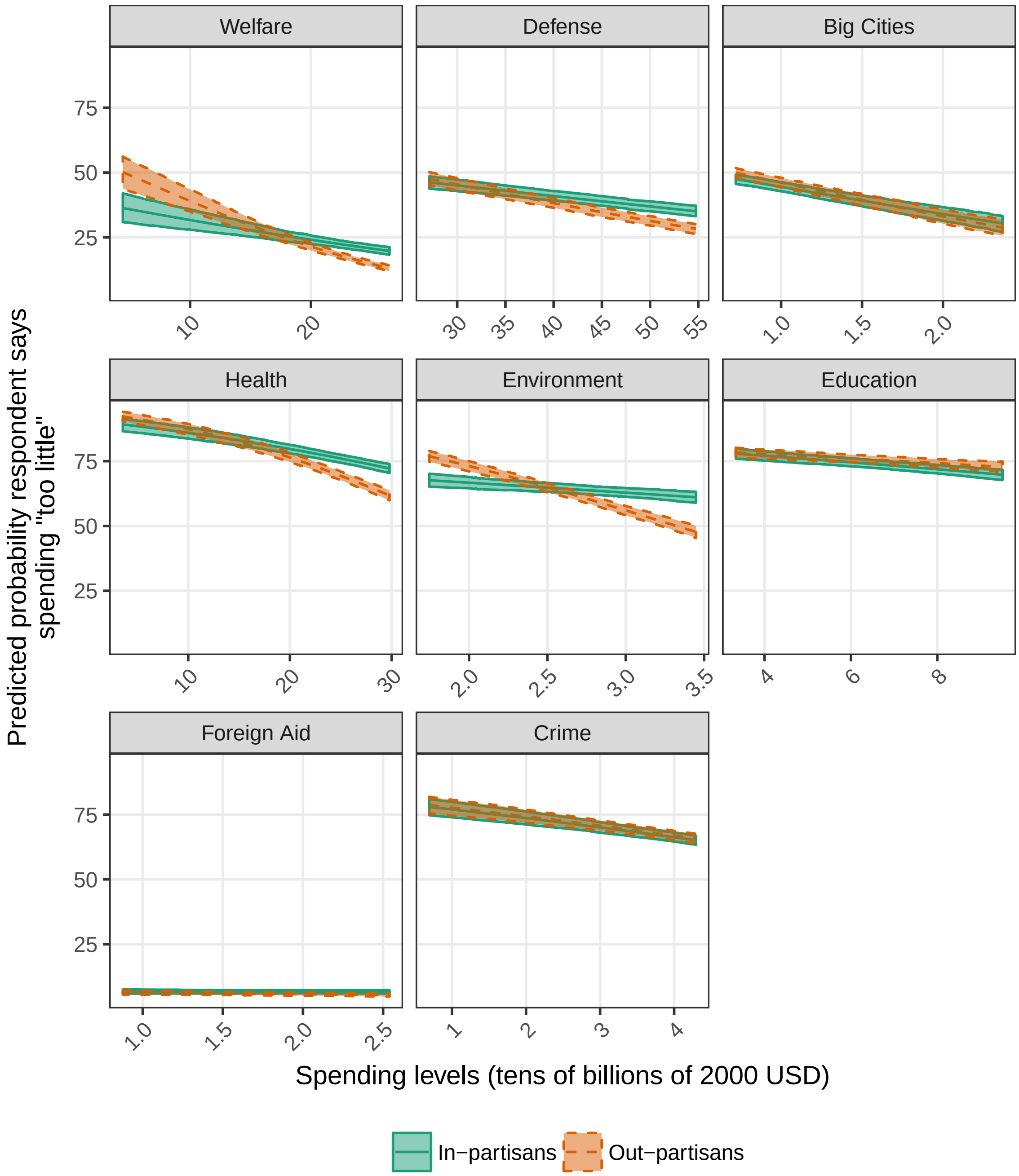

Figure 2: Partisanship and policy feedback. Each panel presents predicted probabilities from Equation 3. As the spending level on a policy increases, the predicted probability of each answer option changes conditional on partisanship.

that in-partisans are less likely to change their stated relative preferences for more (or less) spending as spending changes. In none of the eight policy areas do the results go in the opposite direction of expectations.

These four areas also all exhibit large disagreement across partisan lines (see Table 1). And, although spending on the environment has not historically been a highly divisive issue, in recent years it has become much more divisive, which may account for the differences we see in Figure 2.

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 Table 1), and only moderate 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 Table 1). 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.

6 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 section 3). 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 of the same party as the president are less responsive to policy changes in welfare, health, defense, and the environment 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.

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 opinion 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.

7 References

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A Thermostatic Feedback at the Individual Level

Let us check to see how the thermostatic model works at the individual level. As described in the main text, salient issues are more likely to display thermostatic feedback than nonsalient issues (see also Soroka and Wlezien 2010). 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 expected.

I estimate the model in a Bayesian context separately for each policy area.[15] 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 3 plots the predicted probability of saying “too little” for each of the policy areas.[16] 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.

[15]Sampler diagnostics are reported in Appendix D.

[16]As before, predicted probabilities for “too much” and “about right” are omitted for ease of interpretation. They are reported in Figure 5 in Appendix C. Values for the other variables as well as the scale of the axes are all the same as presented in Figure 3, see footnote 14.

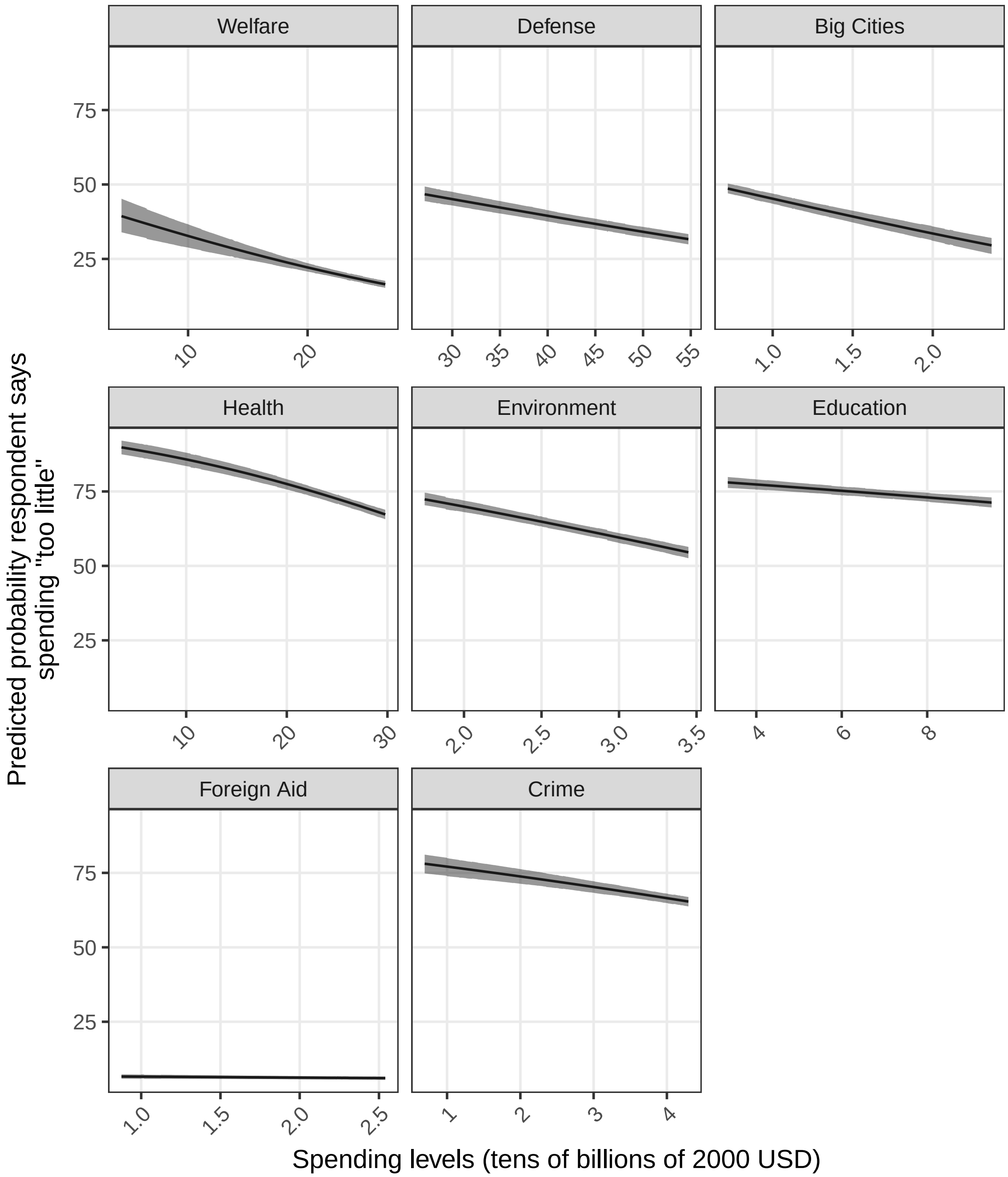

Figure 3: Policy feedback at the individual level. As the spending level on a policy increases, the predicted probability of preferring more spending decreases. Each panel presents predicted probabilities from Equation 2.

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 3 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 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. 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.

B Parameter estimates

Interpretation of regression output for ordered probit models is notoriously difficult. For that reason, I focus on predicted probabilities in the main text. 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

C Figure of all predicted probabilities

In the interest of space and for ease of comparison, I show a figure (Figure 2) in the main text of only the predicted probabilities of saying “too little.” The model, however, also makes predictions for saying “too much” and “about right,” which I report here. Figure 4 reports the same predicted probabilities as Figure 3 including all three response options, and Figure 5 does the same for Figure 2.

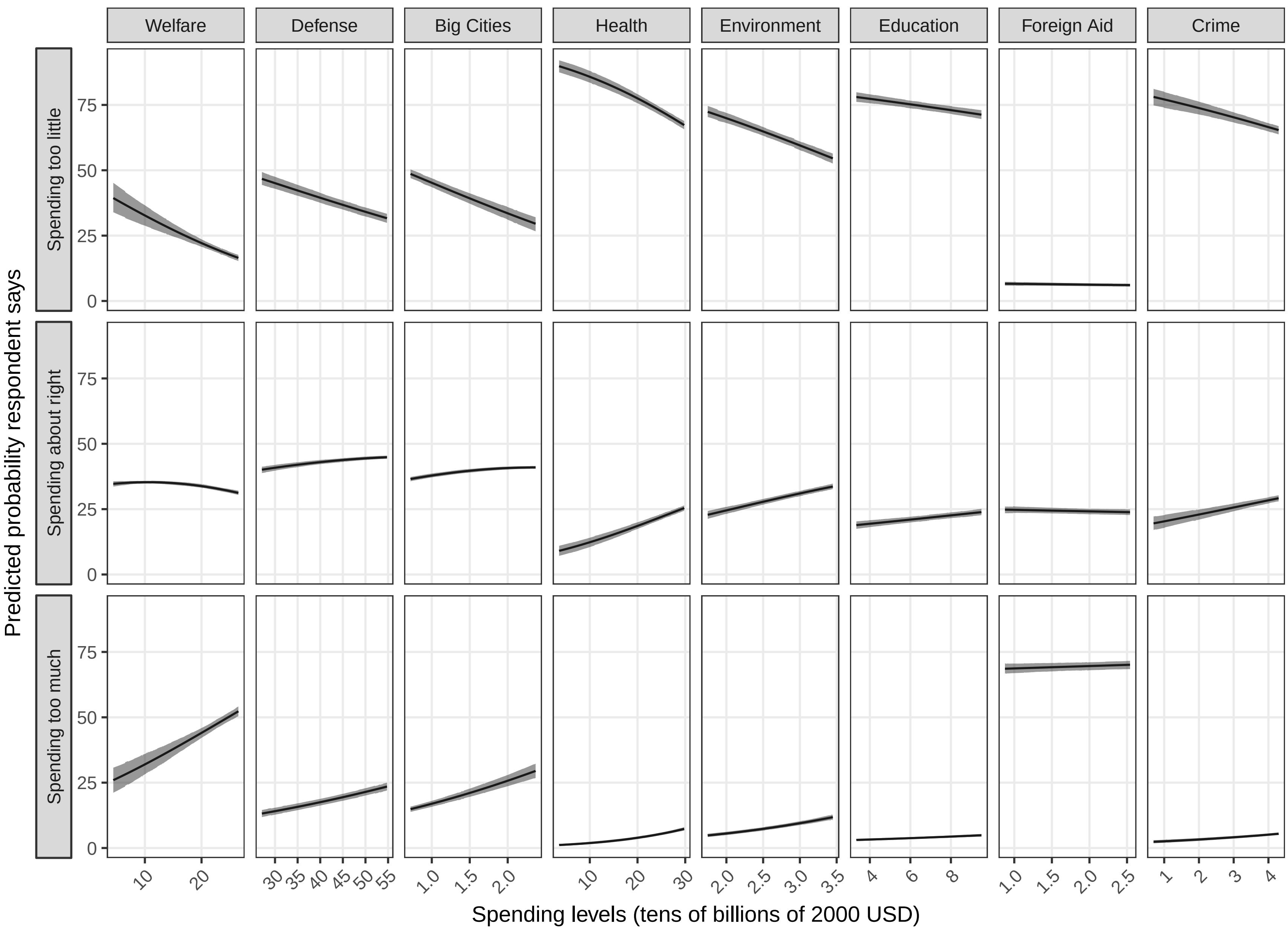

Figure 4: Predicted probabilities for all three answer options

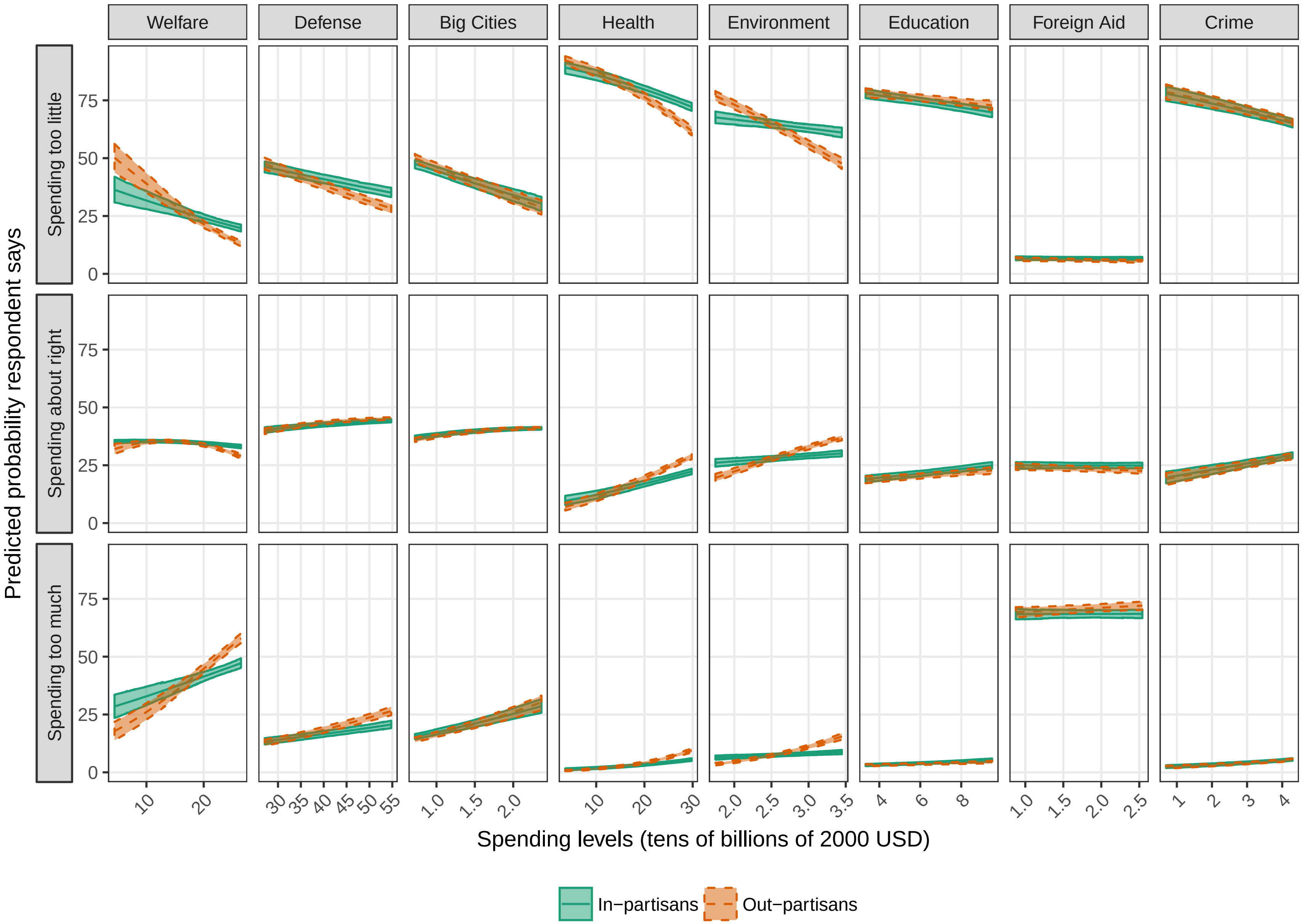

Figure 5: Predicted probabilities for all three answer options

D 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 .

E Partisan News Consumption

In subsection 3.1, I suggest that a logical extension of the work showing that in-partisans trust government more than out-partisans is that in-partisans are less likely to monitor government closely. In this section, I see how plausible that statement is.

In a 2014 study titled, "Local News in a Digital Age,", the Pew Center surveyed approximately 1,000 residents each of Denver, Colorado; Macon, Georgia; and Sioux City, Iowa on their news consumption. To see whether in-partisans consume less news than out-partisans, I rely on two questions. The first asks respondents, "How closely do you follow national news?" and the second asks, "How closely do you follow news about the [Denver/Macon/Sioux City] area?" Response options are on a four point scale ranging from "very closely" to "not at all closely."

It is beneficial to have not only the national news questions but also the local news questions because it permits testing the plausibility of this mechanism at both the national and state level. I code partisans as being "national in-partisans" if they are Democrats (President Obama held office in 2014) and partisans are coded as "state in-partisans" according to whether they matched the party of the governor of their state (Democratic in Colorado, Republican in Georgia and Iowa). I then ran an OLS model predicting news interest at the national level with whether or not individuals were "national in-partisans" and news interest at the local level with whether or not individuals were "state in-partisans."[17] The expectation is that the coefficient associated with in-partisans is negative.[18]

Table 4: In partisans follow news less closely than out partisans

	Dependent variable:			
	national_news		local_news	
	(1)	(2)	(3)	(4)
In partisan, national	-0.075^{***}	-0.082^{***}		
	(0.025)	(0.025)		
Macon		0.011		0.063^{**}
		(0.031)		(0.031)
Sioux		-0.054^{*}		0.070^{**}
		(0.032)		(0.032)
In partisan, state			-0.059^{**}	-0.053^{**}
			(0.025)	(0.025)
Constant	-1.650^{***}	-1.633^{***}	-1.560^{***}	-1.610^{***}
	(0.018)	(0.027)	(0.018)	(0.028)
Observations	3,122	3,122	3,177	3,177
R^2	0.003	0.004	0.002	0.004
Adjusted R^2	0.002	0.004	0.001	0.003
Note:				*p<0.1; **p<0.05; ***p<0.01

[17] I also ran simple differences in means as well as ordered probit models with no difference in the substantive results reported here.

[18] I recoded the variable so that higher values indicate following the news more closely.

Results are reported in Table 4. Each column represents a separate regression, two for the national level (one with fixed effects for the city), and two for the local level (one with city fixed effects). In-partisans report following the news less closely than out-partisans at both the national and state level. This suggests that partisans do in fact monitor the government more closely when they are out-partisans than when they are in-partisans.