The Clues in the News:
Unpacking Thermostatic Responsiveness to Policy[1]

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Abstract: There is a sizeable literature finding evidence of thermostatic responsiveness across a range of salient policy domains and countries. We have only a partial sense for what drives responsiveness to policy change, however. One possibility is that individuals learn what they need to know from the mass media, but there is little work exploring the prevalence of relevant policy cues in media content, or citizens' abilities to pick up on those cues. This paper is the first attempt to examine both, through an automated content analysis of 35 years of defense spending reporting, validated by a coding exercise fielded to survey respondents and expert coders. Results prompt an analysis of a set of ANES questions from 1980-1992, which illustrates how media facilitates thermostatic responsiveness. The outcome is a new perspective on how representative democracy can function, even as both individual opinions and media content are flawed.

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The reciprocal relationship between public policy and public preferences is central to representative democratic governance. That said, there have since the dawn of democracy been real concerns about governments' willingness to respond to citizens, and whether this even makes sense given questions about citizens' ability to provide useful input to governments. Converse's (1964) work has been particularly influential; and there is now a vast literature chronicling the political ignorance of the average citizen (e.g., Berelson et al., 1954; Converse, 1964, 1970; Bennett, 1988; Page and Shapiro, 1992; Delli Carpini and Keeter, 1996; Popkin and Dimock, 1999).

At the same time, there is a growing body of work on "thermostatic responsiveness" suggesting that citizens adjust their preferences for policy change based in part on recent policy (e.g., Wlezien, 1995, 1996; Erikson et al., 2002; Soroka and Wlezien 2005, 2010; Jennings, 2009; Wlezien and Soroka, 2012; Ura and Ellis, 2012; Ellis and Faricy, 2011; Enns and Kellstedt, 2008; Kellstedt, 2003; Bartle et al., 2011). Thermostatic responsiveness is not equally evident in all policy domains, of course. (Indeed, in some domains it is not evident at all.) But in salient policy domains, there is accumulating evidence suggesting that publics can and do respond to policy change, in the US and other countries.

How can we reconcile evidence of thermostatic responsiveness with evidence of uninformed publics? Past work has focused on the advantages of aggregation (see especially Page and Shapiro 1992).[2] This cannot account for thermostatic responsiveness,

[2] Though see Althaus (2003) for a more complicated and less complimentary view of aggregation.

however: it does not explain the underlying trend. Regular citizens do not directly observe national-level policy change, or read the Federal Register for that matter. How then does opinion react to policy change?

This question has been on the minds of scholars of opinion-policy relationships for some time. Consider Barabas' (2011: 194) discussion of Soroka and Wlezien (2010): "At a more micro-level, there is an assumption throughout the book that people get the signal on policy change and then update their preferences accordingly. However, there is no direct examination of media messages or other ways of documenting these linkages." Consider also Hakhverdian's (2012) discussion of the same material: "In the case of Wlezien's original model, the public has to possess knowledge on whether appropriations in defense and domestic domains have gone up or down. The mass media assumedly plays a large mediating role in conveying this message, and with spending data one can perhaps picture people adjusting their preferences for 'more' or 'less' spending based on media information they receive." "Assumedly" and "perhaps" are accurate reflections of the state of the field. This paper represents a first step towards solving this problem.

Our account is very simple, and based on the following propositions: (a) thermostatic responsiveness requires only very basic levels of knowledge about policy and policy change, (b) this very basic information is readily available in media content, and (c) citizens are able to pick up on these informational media cues. This is not to suggest that media are the only means by which citizens learn about policy. Some citizens will have direct experience with certain policies; others may learn about policy change though social networks.[3] It nevertheless seems very likely that media play a central role in facilitating public responsiveness to policy change.

We explore this possibility below, using US defense spending as an expository case. We focus first on a content analysis of roughly 50,000 news stories from 1980 to 2015 – an analysis that finds a surprisingly large number of informational cues about change in defense spending. We validate this automated analysis through coding exercises by both untrained and expert coders. We see these not just as tests of the automation, but tests of whether regular citizens are able to extract information about defense spending from news content. We are buoyed by what appear to be very strong results in both our content-analytic data and coding exercises – both suggest that some basic conditions for mass-media-informed thermostatic responsiveness are met. We then turn to an analysis of a unique set of questions in the 1980-1992 American National Election Studies (ANES), the results of which illustrate how media facilitate thermostatic responsiveness at the individual level.

Mass Media & Thermostatic Responsiveness

Before considering the role of the mass media, it is useful to briefly describe thermostatic public responsiveness, following Wlezien (1995, 2004) and Soroka and Wlezien (2010). If there is thermostatic responsiveness, people would adjust their preferences for "more" or "less" policy in response to policy change, favoring less (more) policy in the wake of policy increases (decreases), other things being equal. Formally, the public's relative preference (R) represents the difference between the public's preferred level of policy (P^*) and policy (P) itself,

[3] Though note that this information, too, likely comes from mass media.

$$R_t = P_t^* - P_t \ , \qquad (1)$$

where the subscripted t indicates time.[4] R can change because either P or P^* changes. Because we often do not have measures of P^*, and also because the three variables are not measured using the same metric, it is necessary to rewrite the equation as follows:

$$R_t = B_1 \, U_t + B_2 \, P_t + e_t \ , \qquad (2)$$

where U is a set of additional exogenous predictors of P^*.

If the coefficient for policy (B_2) in equation 2 is less than 0, we have evidence of thermostatic responsiveness. To be clear: when a government does more in a given policy domain, policy (P) goes up, and preferences for more policy (R) go down, *ceteris paribus*. Past work suggests that this often is true, but it sometimes is not (Wlezien 1995). Moreover, even when the coefficient is less than 0, its size varies, owing partly to characteristics of issues and partly to political institutions (Soroka and Wlezien 2010; Wlezien and Soroka 2012). First, the public is more responsive in highly salient domains. This is intuitive. Second, political context matters. In particular, federalism dampens public responsiveness, seemingly because it lowers the clarity of information about what policymakers are doing at different levels of government.

Thermostatic public responsiveness clearly is important. It provides the basis for holding policymakers accountable. It also provides informed signals that policymakers can effectively represent. Establishing that there is thermostatic public responsiveness, and understanding how it varies across issues and political context, is thus of real significance. There is, as we have noted, a growing body of work that does exactly this.

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[4] The equation can apply across space and time, though the latter is more common and also the focus of the analysis in this paper.

(See citations in the introduction.) But there is little work that seeks to understand the underlying mechanism(s) driving the relationship. We know that most people pay little attention to politics and have little knowledge about it. What we do not know is how people get the information.

What do we know? To begin, we know that thermostatic responsiveness does not require a high level of information. This must be true – otherwise we cannot account for the patterns that existing research detects. Soroka and Wlezien (2010) argue that in many domains people only need to have a sense for the direction of policy change – whether policy has gone up or down – and perhaps also the magnitude – whether it has gone up by a little or a lot. These are very basic informational cues. But even these cues need to come from somewhere.

We also know that policy information is mediated in some way. For many domains, this must be true: people do not typically directly observe what policymakers do. They also don't have copies of the federal budget (or other policies) on their coffee tables, laptops or cellphones. Information about what policymakers do is thus conveyed to the public by some other means, and the most likely suspect is mass media. Although the structure and form of mass media has changed substantially over time, the public still relies primarily on large-scale media organizations for its information about politics.[5]

[5] See, for instance, http://www.people-press.org/2012/02/07/cable-leads-the-pack-as-campaign-news-source/. Of course, citizens may also rely on "new" media for policy information; and these too could facilitate thermostatic responsiveness, particularly if people's various new media sources track policy over time.

That said, the prospect that mass media provide the information that drives the thermostatic model may seem at odds with common critiques of media content. There are considerable bodies of work detailing a range of biases in media content, and a good deal of work lamenting a lack of policy content specifically (e.g., Lawrence, 2000; Bennett et al. 2008), alongside work identifying inadequate and sometimes misleading coverage of complex scientific issue domains in particular (e.g., Friedman et al. 1999; Bucchi and Mazzolini 2003; Stocking and Holstein 2008). Consider also the vast body of work on sensationalism and/or negativity in news content (e.g., Altheide 1997; Davie and Lee 1995; Lichter and Noyes 1995; Meyrowitz 1985; Patterson 1994; Sabato 1991; Soroka 2014). These are just some of the literatures concerned with problems of both the frequency and accuracy of media coverage – they are illustrative of much broader concerns that media content offers a barely perceptible and systematically biased view of public policy.

Just as we argue that citizens may not need much information to form general opinions, we argue that media can be inefficient and biased in many different ways but still provide the basic information citizens need to assess the direction of policy change, at least in very salient policy areas that attract a lot of public, political and media attention. Skeptics abound, to be sure. But there is already work suggesting that people can and do learn about policy when there is sufficient media coverage (see Barabas and Jerit 2009 for both a review of the field, and a new study).[6]

[6] Note also recent developments in work on political knowledge, which we discuss in relation to our own findings in the concluding section.

How can we best explore the possibility that media play a central role in thermostatic responsiveness to policy change? If mass media are one driver of thermostatic public responsiveness, we should be able to identify the following patterns:

1. Mass media content will contain some sufficient number of cues about policy.
2. Mass media cues about policy change will reflect – to some limited degree, at least – what actually happens to policy.
3. Citizens will be able to identify cues about policy change in media content.
4. These policy cues will affect citizens' perceptions of policy change.
5. Citizens' policy preferences will respond (thermostatically) to perceptions of policy change.[7]

The sections that follow examine these five patterns in turn.

Are There Policy Cues in Mass Media?

We begin with an exploration of cues about defense spending available in mass media coverage. We rely on news content in the *New York Times* and *Washington Post*, from 1980 to 2015, using data from Factiva full-text indices. We focus on defense for two reasons: (1) it is a domain for which we have good measures of both relative

[7] Note that the list does not differentiate between the (a) receipt and (b) acceptance of cues, both of which are necessary for public responsiveness (especially see Zaller 1992). To be clear, we explicitly address the former (in item 3) but not the latter. Our analysis still does allow us to test for acceptance, particularly when we examine whether perceptions respond to media cues (in item 4) and then whether those perceptions inform preferences (in item 5). To the extent that media cues affect public perceptions and those perceptions influence preferences, the public must both receive and accept those cues.

preferences and budgetary policy, and (2) it is a highly salient domain for which there is ample evidence of thermostatic public responsiveness (e.g., Wlezien 1995, 1996; Eichenberg and Stoll 2003; Soroka and Wlezien 2010).

We discuss the extraction of relevant media articles in more detail in the Appendix. Note here that our aim was to identify policy-relevant articles in the two newspapers, relying primarily on subject codes in the Factiva database, checked by human coders. Our search produced a database of just over 50,000 stories on defense, which we analyze using Lexicoder 3.0, software designed for large-scale dictionary-based content analyses (Daku et al. 2015; see also Young and Soroka 2012).

We begin with a simple text-cleaning function that removes punctuation and changes all words to lower case. Subsequent analyses rely on both word-count and dictionary-count functions. Our identification of mentions of spending increases and decreases proceeds in two steps: we capture all mentions of *spending*, and then identify the direction of *change* (if there is any). In this section, we focus just on results from the first step, which relies on a simple dictionary search for terms related to spending. (The complete dictionary is included in the Appendix.) Of the 52,805 articles on defense, there are 31,534 articles that include no mention of spending, and 21,271 articles that include at least one mention of spending. Put differently, roughly 40% of our articles include at least one mention of spending. These articles form the body of data on which we will focus our analyses below.

We do not focus on article-level results, however, but rather on sentence-level results. These sentences are identified using a *kwic* (keyword-in-context) function, which both identifies and then extracts (into a separate database) all instances in which a given set of keywords is used. Note that the *kwic* function captures not just the keyword, but the surrounding sentence.[8] From our 21,271 articles with at least one spending mention, we extract a database of 68,873 sentences. These are distributed relatively evenly across years. (See Appendix Table 2 for basic descriptive data on the distribution of articles and *kwic* sentences across years.)

We readily acknowledge that these sentences are a partial, not a perfect, reflection of spending policy content in mass media. Some articles will deal with budgetary policy but not mention "spending" explicitly. Some articles will also focus on policy proposals and arguments, rather than on what spending is actually enacted. These are some of the reasons why our *kwic* entries offer only a partial representation of spending policy content in media. To the extent that our measures miss relevant information, results should understate the degree to which media coverage drives public responsiveness. And for those who suspect that media do not provide any information about budgetary policy, the size alone of the *kwic* dataset should be striking: our corpus amounts to an average of more than 37 defense spending-related sentences every week for the past 35 years. The extent to which these data capture actual spending change is a testable proposition, which we turn to below.

Do Media Cues Reflect Budgetary Policy?

Do media cues actually reflect spending change? We explore this possibility by producing a measure of the "media policy signal" – the direction of policy, as suggested

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[8] The function actually extracts the surrounding x words, for every mention of words in a dictionary. We set a wide, 30-word window here, and in so doing capture the entire sentence in which a set of spending-related keywords are used.

by media content. We begin by identifying all instances in which a spending keyword co-occurs with a direction keyword – for instance, "spend" occurring alongside "more" or "less" offers very clear information about the direction of fiscal policy. Focusing on co-occurrences of spending and direction keywords leaves us with roughly 35,207 sentences in our database that suggest the direction of fiscal policy.[9]

Converting dictionary counts into a media spending policy signal is not necessarily straightforward, but we rely here on the simplest approach: we use co-occurring spending and directional keywords to attribute one of two codes to every *kwic* retrieval, (a) increasing spending (+1), or (b) decreasing spending (-1); we then calculate the sum of all mentions, aggregated by fiscal year, over the 35-year time period.[10]

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[9] More specifically, of the 68,873 sentences on defense spending, 35,207 also include direction keywords.

[10] This approach takes the frequency of co-occurrences as an indication of magnitude, and there may be weaknesses with this method. A month in which there are many co-occurrences in a positive direction will show a strongly positive signal, while a month in which there are only a few co-occurrences in a positive direction will show a weakly positive signal, for instance; and it may not be the case that the magnitude of spending change is systematically related to the number of mentions of upward or downward movement. There still are good reasons to expect a relationship – a larger change in spending is bigger news, after all – but we do not expect a perfect correspondence between our current media signal and fiscal policy. In the absence of a clear alternative, we employ our simple approach, which works quite well, as we will see.

Is there *any* correspondence between media coverage and policy? Are there any hints in these data that media content captures over-time trends in policy? Figure 1 offers a preliminary test, relying on a comparison of our media signal and actual budgetary policy, drawn from the Policy Agendas' database of appropriations.[11]

[Figure 1 about here]

The top panel of the figure shows a simple scatterplot of the media signal in each fiscal year and the corresponding change in appropriations in billions of constant dollars. Each dot represents a fiscal year, and the dashed lines show the zero-point for both axes. (We have data for 32 fiscal years since 1980 because Factiva stories are missing subject codes in three years. See Appendix Table 2 for details.) To the extent that media content points in the same direction as actual spending, we expect dots to appear in either the bottom left quadrant – where spending is decreasing, and media content suggests a decrease – or in the upper right quadrant – where spending is increasing, and media content suggests an increase. Dots in the other two quadrants indicate years in which the media signal is in conflict with the direction of spending. In the top panel we can see that few dots (6 of 32) are in those off-diagonal quadrants, which indicates a strong match

[11] These data are available at policyagendas.org, and have the advantage of using functional definitions that are more temporally consistent than the standard OMB Historical Tables. OMB classification actually changes over time, though probably less often than in other countries, where reliable spending data can be even more difficult to identify (see, e.g., Soroka, Wlezien and McLean 2006).

between the direction of defense budgetary change and the media signal.[12] Indeed, the data suggest a strong relationship in magnitudes as well: the correlation between the two measures is a healthy 0.68. The "Net Media Signal" thus appears to capture the direction and magnitude of spending change relatively effectively (also see footnote 9).

The bottom panel of Figure 1 shows over-time trends in both policy change and the media signal. The dark line shows changes in defense appropriations and the grey line shows our media measure. (The correlation between the two series is of course the same as in the scatterplot, 0.68.) There is no escaping the conclusion that media coverage of defense budgetary policy closely follows actual policy change. Indeed, given the vast body of work on biases and flaws in media coverage – and the very basic approach we use to capture magnitude in our media signal – the relationship in Figure 1 is striking.

We take these results as strong evidence that, on average, media cues in these newspapers reflect what actually happens to policy, at least in the defense spending domain. We accordingly proceed to the next step.

Can Citizens Identify Mediated Policy Cues?

Our first test of whether citizens can identify spending cues in media content comes in the form of a simple coding exercise, fielded in Amazon Mechanical Turk (MTurk). Note that we do not require that MTurkers are broadly representative in this instance –

[12] Note in this instance that the media signal sometimes suggests upward change even as spending shifts downward, but that the opposite is never the case. This bias disappears when we look at spending in current instead of constant dollars. This may suggest that media coverage reports spending without taking inflation into account – though demonstrating this requires more detailed content analysis than we can provide here.

we regard them only as non-expert coders, and examine their ability to identify policy cues in media content.[13]

We selected a sample of media stories as follows. We began with a random draw of 120 stories using the GDEF Factiva subject code from our database. Specifically, we first excluded stories with no spending keywords in order to have stories with at least a minimal amount of policy content. We then divided all articles into three terciles based on the total number of spending keywords and randomly drew 40 articles from each tercile. A single expert coder read through all stories to ensure that they were relevant, i.e., that they dealt with defense spending. We then took a random sample of 40 articles from all articles deemed relevant. In the process of data cleaning we dropped three articles that turned about to be amalgams of what had been published as several different news stories. This left 37 stories which we then inserted into our online coding exercise, built in Qualtrics.

The instructions to MTurkers were straightforward: they were told only that "We are interested in understanding information in news content," that they would be presented with a newspaper article from the last 35 years, and that they should take their time reading before clicking the "next" button. Respondents were then presented with one

[13] The degree to which MTurkers are actually "untrained" is up for debate. They clearly are not trained in the specific task that we require – in that sense, they are closer to regular citizens than they are to expert student coders. At the same time, MTurkers perform online tasks for money, and the most effective ones will be very good at following instructions. It is of some significance, then, that we offer very few instructions in this task.

article randomly drawn from the set of 37. Following the article, they answered several questions, including the following:[14]

Policy Change: Now, thinking about the article you have just read: Did this news article offer any information about changes in government spending on defense (yes, no, unsure);

Direction: Did the article indicate whether spending was increasing or decreasing (increasing, decreasing, unsure);

Magnitude: How would you describe the size of this spending change? On a scale from 1 to 5, would you say that the spending change is… very small to very large.

Note that the *Direction* and *Magnitude* questions were asked conditional on answers to the preceding questions. And note that for this first article, respondents received no information about what they should be looking for in the article. We thus see this first coding attempt as being relatively realistic, in the sense that respondents are reading for no particular reason. They then code a second article, preceded by "Now we would like you to read another article. After reading it you will be asked the same set of questions we asked for the previous article." Now our participants are trained, minimally at least. The extent to which there are differences between the first and second articles is thus of some interest.

This procedure provides us with responses on two articles from roughly 1350 unique US-based MTurkers, and 1767 assessments of defense-oriented stories. We begin our analysis with some aggregate results, specifically, the mean ratings for each of the 37

[14] The titles of questions were not part of the survey; they are included for the sake of exposition here.

articles. We note first that the tendency to report *Policy Change* increases with the number of spending mentions in an article (B = 0.03, p < .001). The idea that reports and mentions are related may seem trivial, but we consider it strong evidence that the cues we capture using Lexicoder-driven dictionary searches are relevant when humans read news articles.[15]

[Figure 2 about here]

Can readers identify not just that there is change, but the direction of that change? The top panel of Figure 2 plots the mean MTurker-assessed *Magnitude*, which effectively incorporates responses to earlier questions on *Policy Change* and *Direction*, and the spending signal from Lexicoder. The line in this panel shows the slope estimated from regressing *Magnitude* on *Net Spending* (B = 0.55, p < .001). The line makes clear the strong relationship between Lexicoder-based results and aggregated MTurk responses: increases in the media measure are associated with aggregate perceptions that spending is increasing. A model that captures the impact of upward and downward cues independently suggests that both are associated with perceptions that spending is

[15] Note that there are some articles for which few respondents identify change, and in twelve of the 37 cases less than half of our sample did so. This can be taken as evidence that the public's ability to receive policy information is limited. It also may highlight variation in the degree to which change is reflected in different stories. Indeed, in some instances, coverage may signal stability more than change, and this may indicate what actually is happening with spending. Whatever the cause, it has little consequence for the analysis that follows, e.g., excluding the twelve cases only slightly improves the relationship between *Policy Change* and *Direction*.

increasing or decreasing. Models that estimate the relationship between logged versions of the net spending measure, and upward and downward cues independently, confirm what the pattern in the figure implies: the relationship is slightly stronger when we allow for a nonlinear relationship. This makes good sense – a shift from one to two cues will likely matter a lot to perceptions in comparison with a shift from four to five. (See Appendix Table 3 for the complete models.)[16]

That said, the task is more difficult for articles that do not contain a clear policy signal. This can be seen in the bottom panel of Figure 2, which shows the same data from the top panel but now highlighting the clear instances of policy change – in this case, the articles with net spending measures either below -2 or above +2. We indicate the zero-points on both axes to make clear that there are very few of these "clear" cases in which the mean MTurk rating is not in the right direction. The grayed-out "unclear" cases produce much more varied ratings, however. Our analyses suggest that these 23 unclear cases are evenly split between what we could characterize as "limited" cases, which include just one mention of spending change, and "mixed" cases, which include a number of both upward *and* downward mentions. (See Appendix Figure 2 for a graphic showing the number of upward and downward cues in all "unclear" cases.) It makes sense that our

[16] Recall also that our coding exercise includes one "untrained" reading of a first story, followed by a "trained" reading of a second. Appendix Figure 1 offers an illustration similar to Figure 2, but comparing results across these first and second readings of each article. The difference in the regression lines for first versus second readings is insignificant. That is, coders are equally good at identifying cues, even when they are untrained.

respondents do not converge on an answer for these articles, as media coverage is not clear about the direction of spending change. This is fairly obvious. But the fact that MTurkers have more difficulty coding when there are fewer spending cues is testament to the fact that the cues captured in our automated analysis matter (to human readers).

We can explore these same data at the individual level as well, and do so using a stacked dataset for which each respondent-article combination is a case. To be clear, we estimate regression models using a dataset that includes two cases for each respondent (where coefficient standard errors are adjusted accordingly, using a pooled OLS panel estimation from the *plm* package in *R*). The models themselves are relatively simple: we regress individual responses for the direction/magnitude measure on either (a) the net spending measure or (b) separate measures of upward and downward spending cues. Note that because direction and magnitude variables are conditional on respondents identifying spending change, these models rely on 1,050 observations of the 37 articles (that is, they exclude instances in which respondents did not identify change).

[Table 1 about here]

Results are presented in Table 1. Models 1 and 2 regress the direction and magnitude of change variable (which potentially runs from -5 to +5, but in our data has a range of -4 to +4) on the Lexicoder-derived net spending measure, and then upward and downward spending cues respectively. Results in Model 1 make clear the strong relationship between the automated cues and individuals' perceptions of policy change; Model 2 shows that respondents are able to identify both upward and downward cues, though are more reactive to the latter.[17]

Model 3 adds an interaction between upward and downward mentions. This allows us to see whether the impact of cues in one direction depends on the existence of cues in the other direction. The magnitude of the coefficients for upward and downward changes thus shift here, as they should; with the inclusion of the interaction term, the direct effect of upward (downward) mentions captures the impact of an upward (downward) mention when the number of downward (upward) mentions is 0. The significant interaction makes clear that the impact of both upward and downward cues is moderated by the presence of cues in the opposite direction. So articles with multiple cues, in multiple directions, make identifying the direction of change more difficult. (This is depicted in Appendix Figure 3, which shows both that the estimated baseline perception of spending is upward, and that the impact of upward or downward cues is moderated by the existence of cues in the other direction.) The results illustrate the complications of multiple cues and also provide further evidence that respondents are sensitive to the kinds of spending cues that we are capturing in automated analyses.

[17] See Appendix Table 4 for two additional models comparing results from first and second mentions independently. Results suggest only a slight (but borderline insignificant) improvement in coding from first to second articles. Results using a nonlinear version of net spending, or upward and downward counts, also point to rather small improvements in fit (as in the aggregate-level results in Appendix Table 3). We accordingly rely on the more readily-interpretable linear measures here.

Expert Coders as a Robustness Check

As an additional validation test – of both the automated coding, and the MTurk coding exercise – we asked three expert (student) coders who were unaware of the contents of the Lexicoder dictionaries to code the same 37 articles, using the same questions provided to our MTurk respondents. Our interest in this instance is whether the expert codes align with both Lexicoder and MTurk assessments.

There clearly are strong correlations between the trained coder assessments and MTurk respondent assessments on the question of whether the article mentions policy change ($r = 0.78$, $p < .001$), the direction of the spending change ($r = 0.88$, $p < .001$), and the magnitude of the spending change ($r = 0.83$, $p < .001$). There also are relatively strong correlations between the Lexicoder-derived measure of policy change and both the trained coder assessments ($r = 0.53$, $p < .01$) as well as the MTurk assessments of the magnitude of policy change ($r = 0.58$, $p < .01$). We take these results as further evidence that untrained coders identify the same information as trained coders, which is a sign that the policy cues we capture are readily understood by human readers.

We rely on expert codings for more qualitative information about policy cues as well. We asked expert coders to identify a sentence in each article that they felt supported their coding of the variables, as a face validity check to see whether human coders are relying on the same sentences that would be picked up through the automated coding. In 35% (9 out of 26) of articles in which two or more coders said spending was changing, all three expert coders chose the same sentence to support their coding choices. In an additional 46% (12 out of 26) of these articles, two coders chose the same sentence.

A qualitative examination of these responses indicates that in 67% (14 out of 21) of the articles in which at least two coders chose the same sentence, these sentences included a spending word co-occurring with an up or down word. For example, in one article identified by Lexicoder as capturing increased spending (a count of 4 when producing our media signal measure), all three expert coders highlighted a sentence in which a spending word (budget) co-occurred with an increase word (boost): "President Bush's defense budget request of $481.4 billion – an 11 percent boost over last year – pushes U.S. defense spending to levels not seen since the Reagan-era buildup of the 1980s." In another example, all three coders chose "The new administration of President-elect Ronald Reagan is committed to increasing military spending and adopting a firm line in dealing with Moscow," which also includes the co-occurrence of a spending word with an increase word. Note that coders were not aware of the dictionary – they were not told to search for specific words. These results then very neatly illustrate the degree to which our dictionaries capture the cues that seem to most clearly indicate the direction of policy change to respondents.

Do Perceptions Reflect Mediated Policy Cues?

The preceding sections make clear the availability of spending cues in media content, and readers' ability to correctly identify those cues. These findings reflect rather simple expectations. When people encounter articles about government spending, they learn how that spending is changing. Recall however that neither the frequency nor reliability with which newspapers provide policy information, or the ability of citizens to pick up on that information in media, is widely accepted. The standard account in both the academic literature and in popular discussions focuses on flaws in media and opinion. These flaws do exist, of course, but our findings indicate that the policy information necessary for thermostatic public responsiveness is both transmitted in coverage and can be received by the public.

Our exploration has nevertheless not yet demonstrated that citizens' policy preferences respond (thermostatically) to the cues about policy they receive through mass media. Although we have seen that spending cues exist, and that they reflect policy, and that citizens can understand them, we lack indications that people actually do receive and accept that information out in the world. That is, we do not know whether individuals' perceptions of policy change are informed by media content. This section addresses this issue.

It does so by leveraging two questions included in seven election waves (both presidential and midterm) of the American National Election Study (ANES), from 1980 to 1992. (To be clear, the surveys are repeated cross sections, not a panel.) Respondents during this period were asked the following two questions:

> *Perceived Spending Change*: Some people believe that we should spend much less money for defense. Others feel that defense spending should be greatly increased. Where would you place what the Federal Government is doing at the present time?
>
> 1. Greatly decrease defense spending…7. Greatly increase defense spending
>
> *Preference for Spending Change (R)*: Some people believe that we should spend much less money for defense. Where would you place yourself on this scale or haven't you thought much about this?
>
> 1. Greatly decrease defense spending…7. Greatly increase defense spending.

Note that these questions tap not only respondents' own preference for increasing or decreasing federal defense spending, but also what they believe the federal government is actually doing. These data thus offer a rare opportunity to examine two important components of the thermostatic model. First, we can assess whether individual-level perceptions of government spending are associated with media content. Second, we can test whether these perceptions of government spending produce thermostatic responsiveness in defense spending preferences. In short: we can assess the connection between media content and relative preferences for policy.

Table 2 shows results of regression models exploring the determinants of *Perceived Spending Change*. (Note that these estimations drop data from the 1980 election, since we have only partial media data for 1979-1980.) This is a seven-point variable ranging from the perception that the government has greatly decreased to greatly increased spending, as noted above. The model includes a basic set of demographic controls: binary variables capturing gender (1 = female) and education (1 = some university or more); a variable capturing income (0 - 4, for 5 income quintiles as defined in the ANES cumulative dataset); and a seven-point party ID variable (where 1 = strong Democrat and 7 = strong Republican). These variables are included only as controls and their effects will not be interpreted in any detail. Most importantly, we incorporate two annual variables: (1) defense appropriations, in constant dollars, over the past year, drawn from the Policy Agendas dataset, and (2) the media policy signal, over the past year, from the content analysis described above. We thus have a multilevel dataset, in which individuals are nested within years. Estimation proceeds accordingly.

[Table 2 about here]

Results in Table 2 indicate that both actual defense spending change and the media signal matter for perceptions of government spending. In Model 1, we can see that changes in defense spending have a significant positive effect on perceptions; that is, when spending increases, people are more likely to perceive a spending increase. Model 2 explores the impact of spending levels in addition to change. Those results demonstrate that levels of spending also have a significant positive effect on perceptions, if smaller and less reliable. It thus appears that public perceptions of defense spending change respond to both the levels of and change in spending. This means that there is a partial mismatch between the question wording (focused on change) and people's responses (based on both change and levels), which is of consequence for our analysis of preferences in the subsequent section, as we will see.

Model 3 adds the media signal, which has a clear positive effect on perceptions, above and beyond the impact of spending itself. Indeed, the inclusion of the media signal, focused on language about change in news content, completely overwhelms the impact of defense spending change, the coefficient for which drops substantially and is not significantly different from zero. This implies that the effect of spending on perceptions is at least partly mediated, for change, at least, which is not surprising given that our measure of media coverage taps spending change. In order to assess whether the effect of spending levels is mediated, however, we need a media measure that reflects spending levels. This is difficult to imagine, let alone construct, but we can simulate one by simply cumulating our media signal over time: since the media signal captures policy change, the running tally of it should capture the sum of policy change. The resulting measure does not literally tap spending levels at each point in time, of course, and it seemingly will differ in the form of an intercept, i.e., the time-serial correspondence should be high.

Model 4 in Table 2 shows results including the cumulative media signal and excluding the spending change variable from this model, as it has no impact once media coverage is added (in Model 3). The new cumulative media variable has a positive, significant effect on respondents' perceptions, and the impact of spending levels goes to zero. Respondents still respond to the media signal tapping spending change, and the coefficients for the two media variables are almost identical, which implies that perceptions about equally reflect coverage of levels and changes in spending. These results support the conjecture that people are responding to media coverage, and not directly to spending per se.

Just how considerable is the effect of media coverage? Consider the following, drawing on results from the final model. The *Media Policy Signal* ranges from -163 to +388 within our sample, with a standard deviation of 187. A 187-unit shift in that signal leads, *ceteris paribus*, to an average 0.187-unit shift in perceptions of government spending – roughly 14% of the standard deviation (1.3) of perceptions of government spending. This is a small but nontrivial amount. And we also must consider the impact of the *Cumulative Media Policy Signal*, which effectively doubles the impact of media coverage on perceptions.

Media coverage clearly does not completely determine perceptions, but it is important. Most importantly, coverage mediates public perceptions of defense spending; it effectively informs people about what government is doing. Given that media content does not exactly follow spending change over time, however, public perceptions of government action are imperfect. (They reflect both spending and the other determinants of content.) That said, there clearly are strong links between policy, the media and public perceptions.[18]

Do Preferences Respond Thermostatically to Perceived Spending Change?

Do perceptions of government policy condition preferences for policy change? This is the subject of the models in Table 3. Here, *Preferences for Spending Change*, also scaled from 1 to 7, as noted above, is the dependent variable. *Perceived Spending Change* is in this instance an independent variable, alongside the same set of demographic and budgetary predictors included in Table 2.

Model 1 in Table 3 shows a model including defense spending levels only, which is the specification implied by the thermostatic model in equations 1 and 2 above. Here we see the significant (albeit at $p<.10$), negative coefficient the model implies: when spending is higher (lower), preferences for spending change move downward (upward). Model 2 adds spending change, which does not influence preferences independent of levels. This also is as we expect given the thermostatic model. Model 3 further adds the

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[18] We also ran a model including an interaction between the *Media Policy Signal* and self-reported media exposure, the results of which indicate that the main effect of the *Media Signal* is no longer significant for those who do not follow the news but the interaction is significant. This is further evidence that the impact of our media measure does reflect exposure to media content.

impact of *Perceived Spending Change*, the dependent variable in Table 2.[19] The coefficient for defense spending levels drops and is no longer statistically significant. Given that Table 2 demonstrates a powerful connection between actual spending levels and perceptions of spending change, this is exactly as we expect.

Results in Table 3 indicate that perceived spending change drives thermostatic public responsiveness. The magnitude of the effect is as follows: the coefficient (-0.186) implies that a one-standard deviation shift in perceptions (1.4 units in this sample) is associated with an average shift in relative preferences of 0.26 – roughly 16% of the standard deviation of the dependent variable.[20] Of course, what ultimately matters is that the

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[19] Appendix Table 5 shows the same models as Table 3, but including another second-order variable, US-Russia Dislike, which is the percentage of Americans who disliked Russia minus the percentage who liked the country. The variable is drawn directly from the data used in Soroka and Wlezien (2010), and is intended to capture variation in perceived security threat. Past work suggests that preferences for spending change are positively correlated with this variable and the results in Appendix Table 5 confirm this. The results suggest that, while preferences do reflect perceptions of spending change, they are more responsive to actual spending, i.e., the public discounts the other influences on perceptions. Note that this is in line with past work, including research by De Boef and Kellstedt (2004) on the influence of media coverage on economic perceptions, which finds that non-political effects on consumer confidence are more meaningful than political ones.

[20] This is comparable to the estimated impact of spending levels themselves: in Model 2, the coefficient (-0.007) implies that a one standard deviation (or 56 billion dollar) shift in

results reveal that people update their preferences based on perceptions of spending, not spending levels per se. Spending still matters, but indirectly, as reflected in media coverage, which influences people's perceptions. That is, it appears that people respond thermostatically to mass-mediated spending change.

[Table 3 about here]

Discussion

This paper has made important headway in unpacking thermostatic public responsiveness to policy. Taken together, the evidence from the automated content analysis, the MTurk- and expert-coding studies, and the ANES analyses, suggest that spending cues exist, that citizens can extract these cues from news content, and that this information matters for perceptions of government spending, and thus to preferences for policy change.

All of this points to the very real possibility that the basic information needed for thermostatic responsiveness to function is readily available. Recognizing this is a significant step towards better understanding the role of media content in public responsiveness, and in representative democracy more broadly. This is not an argument that media perfectly represent policy change or that citizens are deeply informed. It is an indication, however, that even in the presence of flawed reporting, low attentiveness, and misinformation, there are signals in media content that effectively facilitate a form of public responsiveness that is central to a functioning representative democracy.

---

spending produces a -0.39, or 24% of the standard deviation, drop in preferences. Not surprisingly, the estimated impact of perceptions (-0.33) is even closer in magnitude based on results from separate analyses excluding spending levels from the model.

Note that these findings fit with past work identifying some areas in which the public actually has relatively high policy-specific knowledge (e.g., Delli Carpini and Keeter 1997), and, especially, with a recent shift in the literature on political information towards the belief that citizens might be more politically competent than previously thought (e.g., Prior and Lupia 2008; Barabas, Jerit, Pollock, and Rainey 2014). Like this recent work, our results suggest that people can extract and use political information in meaningful ways; and spending change is an aspect of political knowledge that is not captured in survey questions focused on citizens' ability to recall static political facts. To be clear: what we find here does not conflict with the frequently-demonstrated tendency for people to know few specific political facts; it is the product of a rather different kind of political knowledge.

There are some important caveats. We have already looked at correlations between expert- and MTurker-coded news stories above, and seen strong relationships between the two. But we can also take the mean expert code as the "correct" response, and then see how many of our MTurk codes (across all individuals and stories) match this response. Where *Policy Change* is concerned, 57% of MTurk responses correctly identify whether spending is changing. Of those responses, 79% then correctly identify the direction of this change. (Aggregation is thus an important part of the process that gets us to thermostatic responsiveness; though the underlying trend evidently is driven by a large (and diverse) minority receiving relatively reliable mediated cues about policy change. Put differently: our results indicate that many, though not all, citizens can pick up on cues about defense spending in media content.

It is also the case that our results cannot speak to whether preferred levels of policy are "correct." We are not arguing for a rationality in preferences at odds with recent research suggesting that individuals' preferences for levels of redistribution are well below where they should be given individuals' own economic situation (e.g., Bartels 2005), for instance. Our argument focuses entirely on over-time change in preferences for policy change; it cannot speak easily to the possibility that preferred levels are right, or wrong.

The degree to which these finding are generalizable beyond the defense domain is also not clear. There are good reasons to think that defense is an easy case – one in which policy change is often directly linked to (and discussed in terms of) spending, and one that is consistently highly salient. We expect that shifting to a low-salience domain in which a large proportion of policy change is regulatory rather than budgetary, for instance, would produce much weaker results. Indeed, past work already highlights the tendency for low-salience domains to exhibit weaker opinion-policy links (e.g., Wlezien 1995; 2004; Soroka and Wlezien 2010). Our supposition is that this cross-domain variation is partly explained by what is likely much less, and much less clear, media coverage of policy change in these domains. We leave a test of this possibility to future work.

So too do we note, and leave for future research, the possibility that different media sources offer rather different kinds of policy information. We have focused here on two prestigious broadsheet newspapers, and these may be the sources most likely to produce a large number of accurate policy stories. Can we expect the same from the *Houston Chronicle*, the *Huffington Post*, ABC News and an increasingly wide range of online news providers? There surely are important differences in the quantity and quality of policy content across media sources, and the likelihood that individuals respond thermostatically to policy will be affected by their varying news streams.

For the time being, however, we have been able to demonstrate each of the patterns that we expect in order for mass media to play a role in thermostatic public responsiveness. There are a good number of cues about policy change in media coverage of defense spending; these cues reflect changes in budgetary policy; humans are able to identify the cues; individuals' perceptions of policy change shift alongside trends in media coverage; and individuals' relative preferences for policy react thermostatically to their perceptions of policy change. Each of these five patterns is central to the functioning of representative democracy. That they occur, even in one domain, is thus of considerable importance.

That these patterns are evident also serves to highlight the significance of mass media in responsiveness and representation. The argument that the quality and quantity of media are critical to representative government is of course not new – it has been widely accepted, and repeated, at least since *The Federalist Papers*. But the preceding analyses lay bare the potential significance of mass media, and in so doing, this paper elucidates one mechanism underlying thermostatic public responsiveness, a widely accepted but as-yet largely unexplained element of functioning representative democracy.

Appendix

Media Content

We rely on the Factiva subject keyword GDEF to identify articles. This topic was selected based on preliminary searches; it tends to be policy-focused rather than just focused on wars.

Note that the use of Factiva keywords by no means perfectly captures only relevant articles. We invariably miss some relevant articles; and our analyses identify a good volume of irrelevant material captured in our searches as well. The keyword search is nevertheless more efficient than a full-text keyword search. Of course, Factiva's assignment of topics is most likely a function of their own dictionary-based word search, but our assumption is that their search is more developed than ours would be. We suspect that our use of their keywords means that we err on the side of Type I rather than Type II errors. That said, we have to sort through irrelevant material as well, and one aim of the analyses that follow is to improve our ability to identify relevant material.

A more critical issue with subject codes in Factiva is that they have not been applied to all years – there are in particular years in the late 1990s when no subject codes exist for either of the newspapers that we focus on, and we thus have missing data in these years. For this preliminary work, we simply work around these missing data. That said, we do not lack for media content. Our database includes roughly 52,800 defense articles. The basic breakdown of articles is shown in Appendix Table 1, which reports the total number of articles downloaded by newspaper and decade.

[Appendix Table 1 about here]

The table makes clear the gaps that result from the intermittent non-existence of subject codes in the Factiva database. We have no *Washington Post* articles before 2000. (There are also articles missing from Table 1 due to miscodes for date and/or news source, but these cases are relatively rare.) For the time being, we work with these data, with the belief that they will give us a sufficient sense for whether policy cues are available, and retrievable, in media content.

Content-Analytic Dictionaries

Dictionaries used above are implemented in Lexicoder, and constructed from our own reading of *kwic* retrievals, augmented by thesaurus searches. They are as follows:

```
SPENDING: allocate*, appropriation*, budget*, cost*, earmark*, expend*, fund*, grant*, outlay*, resourc*, spend*
UP: accelerat*, accession, accru*, accumulat*, arise*, arose, ascen*, augment*, boom*, boost, climb*, elevat*, exceed*, expand*, expansion, extend*, gain*, grow*, heighten*, higher, increas*, increment*, jump*, leap*, more, multiply*, peak*, rais*, resurg*, rise*, rising, rose, skyrocket*, soar*, surg*, escalat*, up, upraise, upsurge, upward
DOWN: collaps*, contract*, cut*, decay*, declin*, decompos*, decreas*, deflat*, deplet*, depreciat*, descend*, diminish*, dip*, drop*, dwindl*, fall*, fell, fewer, less, lose, losing, loss, lost, lower*, minimiz*, plung*, reced*, reduc*, sank, sink*, scarcit*, shrank, shrink*, shrivel*, shrunk, slash*, slid*, slip*, slow*, slump*, sunk*, toppl*, trim*, tumbl*, wane, waning, wither*
```

Note that not all direction words will be used in relation to spending; just as not all spending mentions will co-occur with direction keywords. We start by casting a relatively wide net in both instances, however; and expect that the concurrence of these two dictionaries will identify sentences that are related to policy direction in each domain.

Additional Tables and Figures

[Appendix Figures 1-3 about here]

[Appendix Tables 2-5 about here]

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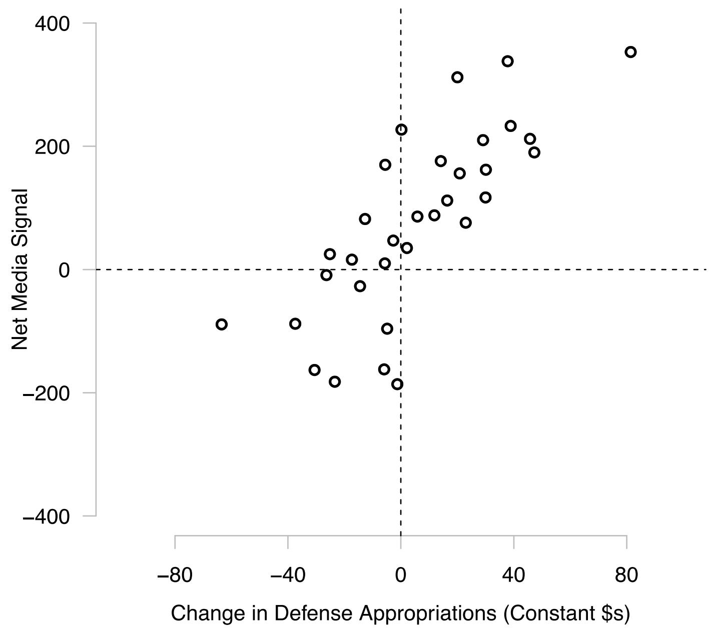
Figure 1. Media Cues and Budgetary Policy



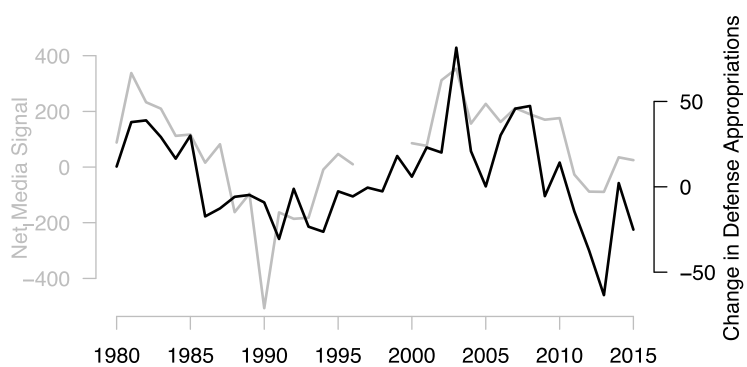
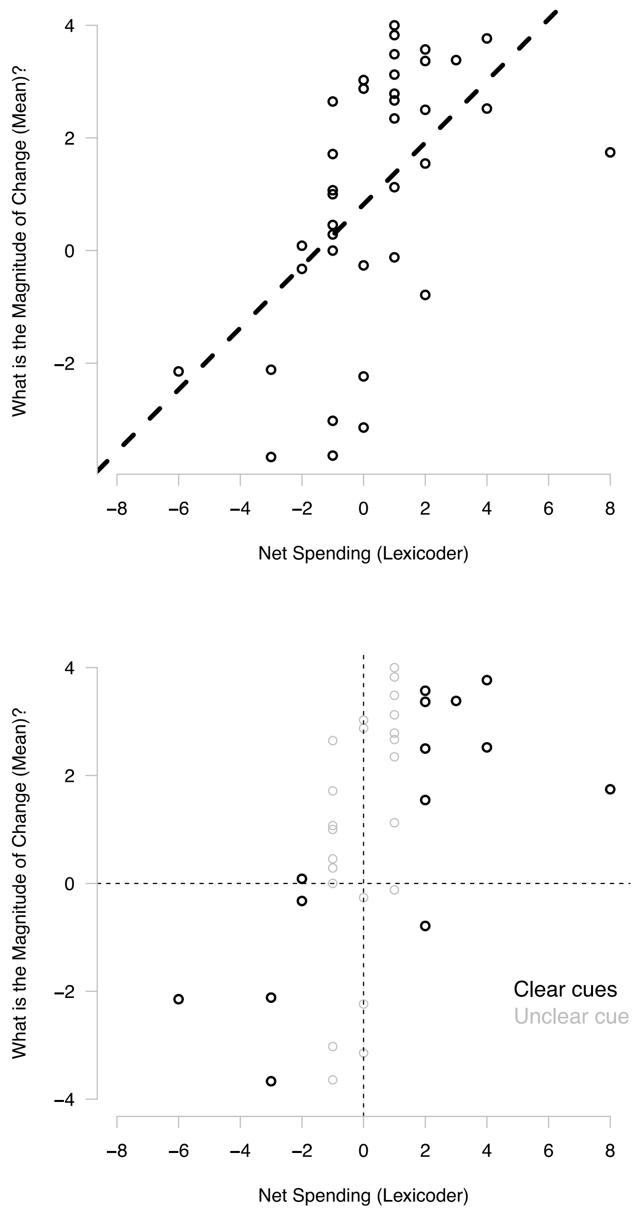
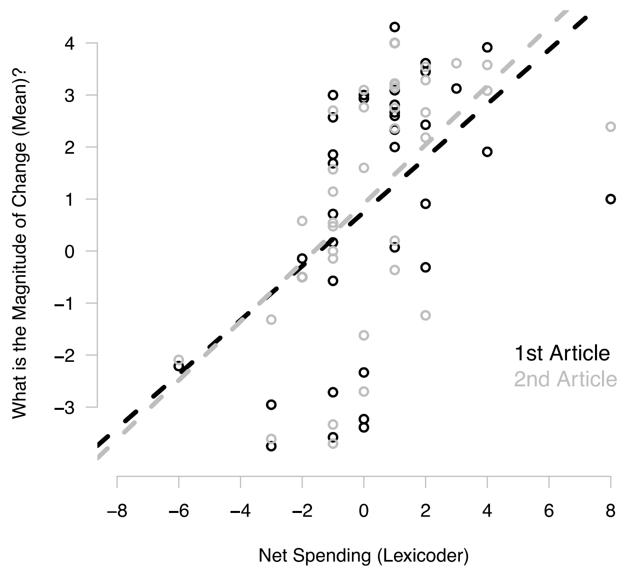


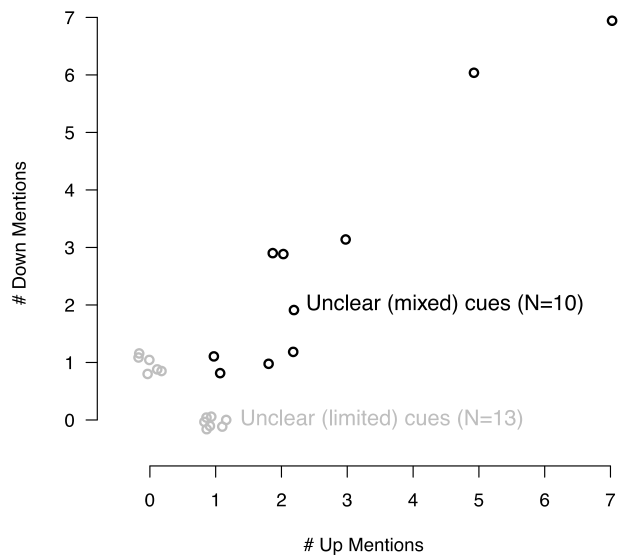
Figure 2. Media Cues and Aggregated MTurk Ratings of the Magnitude of Policy Change



Appendix Figure 1. Media Cues and MTurk Ratings of the Magnitude of Policy Change, First versus Second Codings



Appendix Figure 2. Upward and Downward Mentions in Unclear Articles



Appendix Figure 3. The Impact of Combinations of Positive and Negative Cues on Perceived Direction and Magnitude of Change

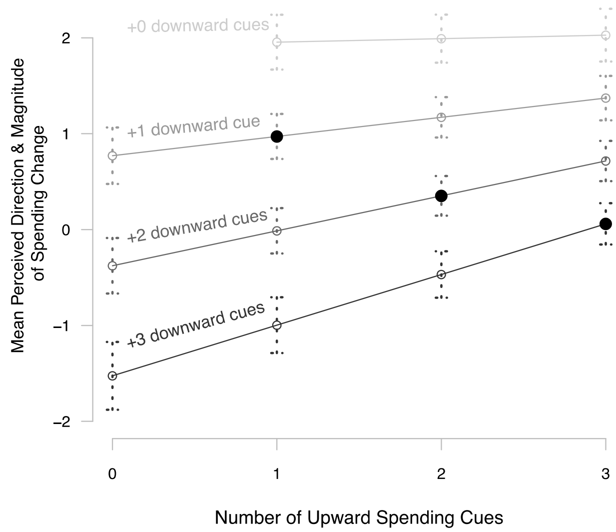


Table 1. The Direction and Magnitude of Change and Spending Cues

	Model 1	Model 2	Model 3
Net spending mentions	.533***		
	(.037)		
Upward spending mentions		.457***	.036
		(.047)	(.064)
Downward spending mentions		-.590***	-1.148***
		(.038)	(.078)
Upward * Downward mentions			.164***
			(.019)
Constant	.596**	.957***	1.918***
	(.094)	(.155)	(.187)
N	1050	1050	1050
R2	.175	.182	.237

Cells contain regression coefficients and robust standard errors from an OLS panel estimation. * p < .10; ** p < .05; *** p < .01.

Table 2. Modeling Perceptions of Spending Change, ANES, 1982-1992

	Model 1	Model 2	Model 3	Model 4
Female	0.108**	0.103**	0.099**	0.099***
	(0.048)	(0.048)	(0.048)	(0.028)
Education	0.128**	0.135**	0.135**	0.140***
	(0.055)	(0.054)	(0.056)	(0.029)
Income	-0.009	-0.006	-0.004	-0.004
	(0.010)	(0.009)	(0.009)	(0.013)
Party ID	-0.078***	-0.080***	-0.083***	-0.083***
	(0.005)	(0.005)	(0.006)	(0.007)
Defense Spending Change *t*	0.033**	0.032***	-0.003	
	(0.013)	(0.008)	(0.013)	
Defense Spending Levels *t*		0.004**	0.005***	-0.001
		(0.002)	(0.001)	(0.001)
Media Policy Signal *t*			0.002**	0.001***
			(0.001)	(0.0001)
Cumulative Media Policy Signal *t*				0.001***
				(0.0001)
Constant	5.106***	3.494***	3.263***	4.908***
	(0.115)	(0.590)	(0.338)	(0.284)
N	8802	8802	8802	8802
R2	0.052	0.064	0.072	0.078

Cells contain regression coefficients and clustered standard errors from an OLS panel estimation. ***p < .01; **p < .05; *p < .1

Table 3. Modeling Relative Preferences for Spending Change, ANES, 1980-1992

	Model 1	Model 2	Model 3
Female	-0.185***	-0.188***	-0.169***
	(0.054)	(0.052)	(0.054)
Education	-0.483***	-0.482***	-0.457***
	(0.060)	(0.058)	(0.065)
Income	0.027*	0.026	0.024
	(0.016)	(0.016)	(0.016)
Party ID	0.184***	0.185***	0.168***
	(0.012)	(0.012)	(0.014)
Defense Spending Levels *t*	-0.006*	-0.007*	-0.005
	(0.004)	(0.004)	(0.003)
Defense Spending Change *t*		0.017	0.023
		(0.021)	(0.019)
Perceived Spending Change			-0.186***
			(0.036)
Constant	5.855***	5.921***	6.346***
	(1.415)	(1.439)	(1.373)
N	9857	9857	9857
R2	0.111	0.116	0.139

Cells contain regression coefficients and robust standard errors from an OLS panel estimation. ***p < .01; **p < .05; *p < .1

Appendix Table 1. Sample of News Articles, by Decade and Newspaper

	Defense	
	NYT	*WPost*
1980s	15312	0
1990s	3382	14
2000s	10667	10346
2010s	5572	5807

Appendix Table 2. Media Cues, Annually

FY	Articles per year	Articles with spending cues	Sentences with upward spending cues	Sentences with downward spending cues
1980	425	168	216	90
1981	1293	578	896	479
1982	1538	635	764	465
1983	1586	701	955	680
1984	1532	612	603	459
1985	1947	831	906	767
1986	2080	825	670	641
1987	1960	707	534	423
1988	1441	607	594	772
1989	1228	520	531	603
1990	1045	488	525	1046
1991	1042	417	335	494
1992	690	321	274	453
1993	815	368	275	447
1994	777	317	214	217
1995	678	296	332	257
1996	273	126	77	57
1997	42	20	*NA*	*NA*
1998	14	9	*NA*	*NA*
1999	4	2	*NA*	*NA*
2000	528	260	202	92
2001	647	258	220	118
2002	1382	576	562	225
2003	2779	975	852	407
2004	2222	832	579	364
2005	2504	970	758	454
2006	2472	891	655	419
2007	2992	1119	737	424
2008	2496	991	652	382
2009	2374	949	693	458
2010	1999	849	594	365
2011	2143	871	635	588
2012	2302	994	725	761
2013	2473	1012	596	634
2014	2058	797	458	391
2015	1022	379	199	143

Appendix Table 3: The Direction and Magnitude of Change and Spending Cues

	Using linear mentions		Using logged mentions	
	Model 1	Model 2	Model 1	Model 2
Net Spending Mentions	0.548***		1.476***	
	(0.138)		(0.306)	
Upward Spending Mentions		0.428**		1.347**
		(0.165)		(0.550)
Downward Spending Mentions		-0.634***		-2.184***
		(0.152)		(0.460)
Constant	0.820**	1.278**	0.799**	1.417**
	(0.326)	(0.476)	(0.304)	(0.593)
N	37	37	37	37
R-squared	0.310	0.343	0.397	0.399

***p < .01; **p < .05; *p < .1

Appendix Table 4. The Direction and Magnitude of Change and Spending Cues, First and Second Articles

	First Articles			Second Articles		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Net Spending Mentions	0.516***			0.550***		
	(0.058)			(0.049)		
Upward Spending Mentions		0.434***	-0.030		0.481***	0.098
		(0.074)	(0.104)		(0.059)	(0.078)
Downward Spending Mentions		-0.581***	-1.208***		-0.600***	-1.099***
		(0.057)	(0.113)		(0.052)	(0.107)
Upward * Downward Mentions			0.183***			0.147***
			(0.029)			(0.025)
Constant	0.398***	0.800***	1.871***	0.771***	1.094***	1.959***
	(0.140)	(0.235)	(0.286)	(0.130)	(0.204)	(0.240)
N	493	493	493	557	557	557
R-squared	0.162	0.171	0.235	0.190	0.196	0.243

Cells contain regression coefficients and robust standard errors from an OLS panel estimation. * $p < .10$; ** $p < .05$; *** $p < .01$.

Appendix Table 5. Modeling Relative Preferences for Spending Change, ANES, 1980-1992

	Model 1	Model 2	Model 3
Female	-0.198***	-0.202***	-0.184***
	(0.052)	(0.052)	(0.053)
Education	-0.473***	-0.463***	-0.440***
	(0.058)	(0.058)	(0.065)
Income	0.027*	0.032**	0.030**
	(0.015)	(0.014)	(0.015)
Party ID	0.184***	0.179***	0.164***
	(0.013)	(0.012)	(0.013)
US-Russia Dislike *t*	0.008***	0.020***	0.020***
	(0.002)	(0.003)	(0.003)
Defense Spending Levels *t*	-0.007**	-0.007***	-0.005***
	(0.003)	(0.001)	(0.001)
Defense Spending Change *t*		-0.068***	-0.059***
		(0.012)	(0.008)
Perceived Spending Change			-0.172***
			(0.025)
Constant	5.866***	5.610***	6.014***
	(1.049)	(0.316)	(0.293)
N	9857	9857	9857
R2	0.139	0.161	0.180

Cells contain regression coefficients and robust standard errors from an OLS panel estimation. ***p < .01; **p < .05; *p < .1