Appendix for:
Heuristics in Context

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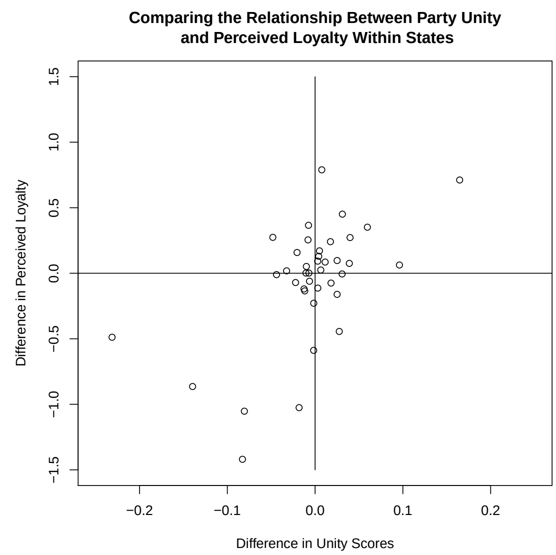
A1: Comparing voters' perceptions of senatorial party-line voting between intra-state senator pairs

Figure A1.1



In Figure A1.1 we provide evidence from the full sample of state senatorial pairs that were illustrated for three selected cases in Table 1. Specifically, the x-axis on this plot is the difference in the historical party unity scores for the two senators in a given state. A negative sign means the first senator's score was smaller and a positive sign means the second was smaller (the choice of first or second senator is arbitrary and inconsequential). The y-axis is a measure of the difference in the voters' perceived party loyalty between the two senators over all seven issue areas. Again, a negative sign means perceptions of the first senator's loyalty were less than perceptions of the second senator's loyalty, while a positive sign means perceptions of the second senator's loyalty were less. Thus, if our hypothesis that voters perceive senators with less partisan unity as more likely to vote against their party on the bills in question, then we would expect the signs of these two variables to be the same (i.e., the cases should all fall in the North East and South West quadrants of the figure). And indeed, the data seem to support this expectation. If we allow for some measurement error (thus ignoring the cluster of points around 0,0 in the figure, we see that in almost all cases in which there was a significant difference in unity scores between two senators in a state (say difference bigger than about .05 in absolute value), voters' perceptions of how the senators voted on the bills in the survey differed in exactly the way we would expect. Only in cases in which unity scores were not very different from one another did we get any cases in which the senator with the smaller party unity score was perceived to vote the party line more often. Further, with perhaps two exceptions (the two dots somewhat farther out in the NW and SE quadrants respectively) the differences in voter perceptions for these senators were also small. Thus, we are comfortable attributing these "exceptions" to our prediction to measurement error.

A2: Specification and estimates for the model presented in the text

Operationalization of the theoretical variables for inclusion on the right-hand side

As discussed in the text, the simple logic of our empirical test is a comparison of the substantive effects of party position (and true vote) on respondent beliefs across different contexts. Given the multinomial specification of the model, however, the specification of the empirical model is complicated in a number of ways.

First, the data set is complicated by the fact that not only does each respondent answer for two senators and seven issues (as discussed in the text), but the conditional logit model that we use (both in its random effects and non-random effects variants) requires that each of these respondent-choices be represented by three lines of data: one for a "yea" response, one for a "nay" response, and one for "don't know." The dependent variable is simply and indicator marking which of these alternatives is chosen in a given respondent-choice. Second, many of our variables are nominal in nature so enter the model as sets of dummy variables (e.g., the senators' true vote is captured by a dummy for "yea," a dummy for "nay," where we exclude the "abstain" category).

First, since characteristics of respondents, issues, and senators do not vary over alternatives, estimation of the effects of such variables in the conditional logit model (and also the random-effects conditional logit— i.e, the mixed logit) requires that they be interacted with alternative-specific indicator variables before entering the model. Specifically, one alternative is chosen as a baseline (in our case, the DK response) and each covariate is interacted with indicators for the other two choices. Thus, for every variable included in the estimation, we report coefficients on two constructed variables — one interacted with an indicator for the "yea" alternative (reported in the first set of columns in each table) and one interacted with an indicator for the "nay" alternative (reported in the second set of columns).

Second, some of our covariates are nominal and so also enter the model (before the interactions discussed in the last paragraph) as sets of indicator variables. For example, true vote has three possible values — "yea," "nay," or "abstain" — and so we include indicators for "yea" and "nay." Likewise, party position has two categories — "yea" and "nay" — so we include one indicator for "yea".

Finally, to capture the logic of our hypothesis many of these sets of dummy variables must be interacted with each other. This leads to a complicated "right-hand-side" in our model. To help readers navigate these complications Table A2.1 provides a map between the conceptual variables and the way they are actually operationalized in the main model that we talk about in the text (other models reported in the robustness section below are subsets of the variables detailed in Table A2.1). This table provides all the relevant information about the variables used in the specification reported in the text (other than demographics and issue fixed effects). The table is organized by concept (the shaded cells) and then provides the exact variable or set of variables used to operationalize the concept in the empirical model. The chart also includes some descriptive information about the variables where appropriate. The columns in the table specify which categories of covariates and which category of the dependent variable where used as baselines. Since these categories are excluded from the estimation for identification, no coefficients are estimated for them. For each of the empty cells in the table, however, we estimate one coefficient. These are the coefficients reported in the results table which follows (i.e., Table A2.3).

Understanding the Grouped Structure of the Data

In addition to the operationalizations mapped out above, and as we explained in the text, we also needed to consider the hierarchical, or grouping, structure of the data. In our survey, each respondent indicated whether they believed each of their senators voted for or against each issue or said "Don't Know." This configuration means that each respondent contributes 14 observations to the data that are grouped variously by senator (once for each issue for each of their two senators). This structure is illustrated in Table A2.2 below.

In the language of hierarchical data structures, senators and issues are perfectly crossed: that is, each senator is evaluated with respect to every issue and every issue is evaluated for each senator. Respondents and issues are also perfectly crossed, as are states and issues. Senators and respondents are imperfectly crossed: several respondents evaluate each senator, but each pair of senators is evaluated by a different set of respondents — senators and respondents are perfectly crossed within states, however.

Logically, the data structure illustrated in Table A2.2 leads to a variety of natural groupings at which unmeasured variables could impact the probability of a respondent reporting (for a given issue for a given senator) "yea," "nay," or "Don't Know."[1] The four main groupings are as follows:[2]

1. State Level: unmeasured factors that have the same impact on the probability of choosing yea, nay, or DK for all respondents, issues, and senators in the same state, but that vary across states.

2. Senator Level: unmeasured factors that have the same impact on the probability of choosing yea, nay, or DK for all respondents and issues responding for the same senator, but that vary across senators (within the same state or across states).

3. Issue Level: unmeasured factors that have the same impact on the probability of choosing yea, nay, or DK for all respondents responding for the same issue (no matter which senator they are answering about) but that vary across issues.

4. Respondent Level: unmeasured factors that have the same impact on the probability of choosing yea, nay, or DK for all issues and senators about which a given respondent responds, but that vary across respondents. So these are unmeasured individual characteristics that impact all of a respondent's answers in the same way.

In addition to these main levels, combinations of these levels are possible (e.g., one can think of unmeasured factors that would add a common variance component to observations that shared a senator-issue- where this component would be distinct from either the senator variance component or the issue variance component). This then brings the number of possible natural crossed groupings in the data to nine.[3] Further, in addition to these natural groupings in the data, the fact that there are three rows of data for each respondent-choice allows one to identify and additional (somewhat artificial) grouping for each choice. By treating each choice as a group of three observations,

[1]This structuring assumes there are no party-level factors. Though some may take issue with this, recall that we model the voters' orientation toward the party of their senator (party agreement). Further, examination of the data reveals no significant effects at the party level.

[2]In addition to these main levels all the different combinations of the levels could also generate common error components. So, for example, we can imagine a Senator-Issue grouping in which there are unmeasured factors that have the same impact on the probability of choosing yea, nay, or DK for all respondents but that vary across senators-issues. Thankfully, we find little evidence that these combinations have much impact on our estimated beyond that caused by the error components representing their constituent parts. In the diagnostic analysis presented in the appendix, we illustrate this with one such combination (issue-senator) that we thought most likely to influence the estimates. As with other combinations, however, our diagnostics make it clear that any issue-senator effect follows closely the impact of senator on its own.

[3](1) State, (2) senator, (3) issue, (4) respondent, (5) state-issue, (6) senator-issue, (7) issue-respondent, (8) senator-respondent, (9) senator-issue-respondent.

mixed logit models allow one to estimate random coefficients and intercepts at the choice level (so allowing estimates of individual choice level heterogeneity, see Revelt and Train 1998). In our case, that simply means that we can estimate random effects that will allow each respondent-choice to deviate idiosyncratically from others due to unmeasured factors at the respondent-choice level (or, importantly, at any of the nine higher levels).[4]

Estimating a nine-level hierarchical model with the crossed-effects described above is not feasible with current techniques (especially given our categorical dependent variable). However, as we discussed in the text, we should not be equally concerned about each of the logical groupings in the data. For example, our intuition is that there are few unmeasured variables at the state level that push all voters in a given state to answer questions about all issues, for both their senators, similarly. In contrast, it is easy to think of unmeasured factors that might impact all respondents' responses about a given issue (say, for example, that it received a lot of negative news just before the survey). Likewise, we might be concerned that unmeasured characteristics of a given respondent would lead her to answer all her questions (for each senator) similarly (e.g., be more likely to say don't know or just say "yea") — though, given our controls for demographics, issue preferences, partisanship, and political interest, it is also plausible that there are few relevant unmeasured respondent characteristics. In section A3 of this appendix, we provide some analysis that helps us identify which natural groups in the data are likely to lead to inferential problems and so which groups need to be accounted for in the empirical model (and in what ways). But, in the end, our main model included all the covariates in Table A2.1, a set of standard demographics about respondents, fixed effects for issues (bills) and random effects for responses (i.e., respondent-issue-senator). The coefficients from this model are reported in Table A2.3 below:

[4]This means, of course, that one estimation strategy would simply be to allow random effects at this respondent-choice level and no others. Higher-level error components would then be manifest in similarities in the estimates for different respondent-choice level random effects (i.e., if observations about the same senator shared some common error component, estimates of respondent-choice intercepts for these groups of observations should be reflect that).

A3: Exploring the impact of groupings in the data

In this section, we present key results from the diagnostic analysis we did to settle on the specification of random and fixed effects that we presented in the main text. Specifically, following King and Roberts (2012) we examined estimates from our main model (Table A2.3) where rather than including any the fixed and random effects, we instead estimated standard errors that were clustered on the various groupings described above. What we are looking for in doing this is how much (and in what ways) the estimated standard errors change (from the baseline of non-clustered standard errors in a model with no fixed or random effects) when clustered on different groups. Where there are large changes, we should be concerned that correlations induced by unmeasured factors at that level will impact our inferences if not accounted for (i.e., by introducing better measured covariates at that level, or including appropriate fixed or random effects). In addition, we will be interested in whether clustering on different groupings (e.g., all rows of data from the same state vs., all rows of data for the same senator) produces the same or different patterns of changes in standard errors, since different groupings that produce the same patterns may be accounted for with the same modeling strategies.

Figure A3.1: The Frequency of Differences in SE's of Coefficients from Model in Table A1 when Using Robust Standard Errors Clustered on the Indicated Group Compared to Non-Clustered Standard Errors (positive numbers indicate the Clustered SE is bigger).

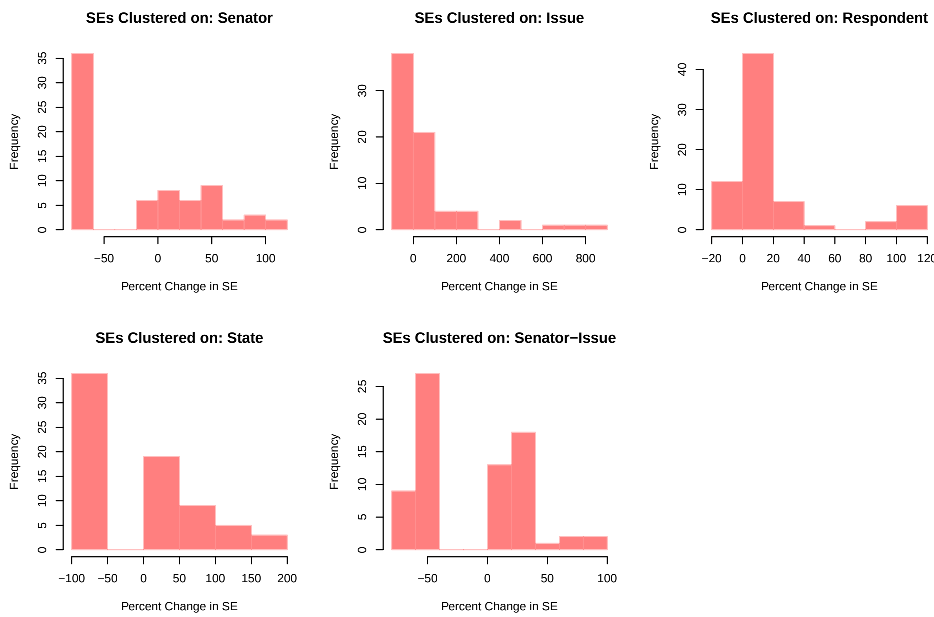


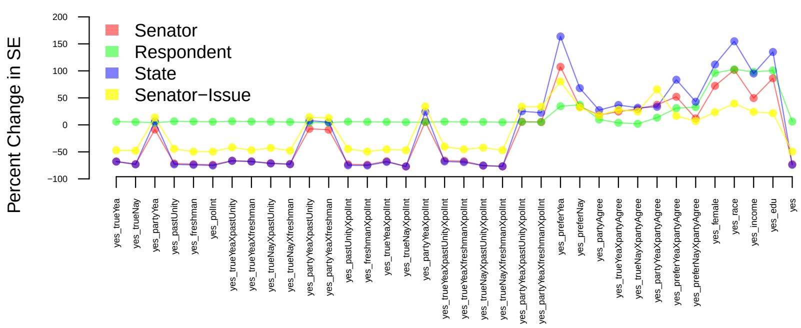
Figure A3.1 provides a first cut at characterizing the differences in estimated standard errors clustered on different groupings. This just gives histograms of the frequency of different percentage changes in standard errors (over the various estimated coefficients). So, for example, when grouping on Senator there are relatively few coefficient's whose standard errors change by more than 100%, while there are many such changes when grouping on issue.

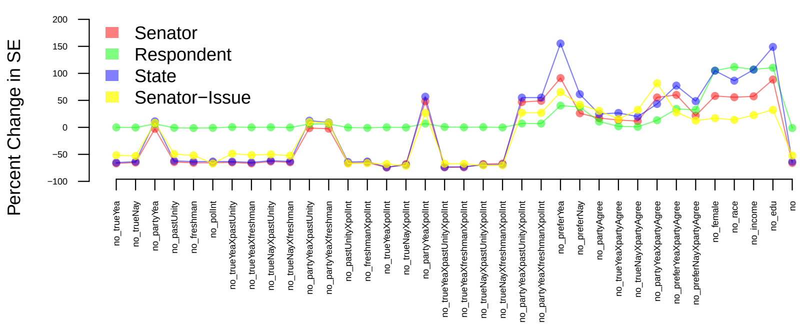
Clearly, looking at all the estimated coefficients together, clustering on issue creates much greater differences in standard errors than clustering on other groupings in the data. Likewise clustering on respondent is by far the least consequential, which suggests we have included a sufficient set of measured characteristics of respondents to capture commonalities in the way a given respondent answers the various issue questions for each of his or her senators. Others groupings fall in between these.

The next figure (Figure A3.2) shows the pattern across variables of changes in estimated standard errors when clustering on different groupings. We can also see that the specific standard errors that seem to be impacted the least among our various coefficients are the set of coefficients on our variables of most interest (the bold variables in Figure A3.2): those indicating the importance of the senator's party's position on the respondents' response (i.e., those directly testing our hypotheses about the *partisanship heuristic*).

Finally, we can see that the pattern of differences across coefficients is very similar for senators and states, as well as senator issues — suggesting that the impacts of these groupings on the correlations in the data are quite similar and so may be remedied efficiently by modeling only one of these groups. Recall that in the end, however, we choose to model the error at the choice (or senator-issue-respondent) level, which effectively subsumes all other levels or potential error from unmeasured variables.

Figure A3.2: Percentage Difference in SE's of Coefficients from Model in Table A1 when Using Robust Standard Errors Clustered on the Indicated Group Compared to Non-Clustered Standard Errors (positive numbers indicate the Clustered SE is bigger). Categories on the x-axis indicate variables in the model. The Issue grouping is excluded due to the extreme scale of its differences (the pattern is the same but more extreme)





Section A4: Robustness checks

A simple specification

In this section we present the results for the vastly simplified empirical model that was discussed in the text. This model is in some sense on the opposite side of the spectrum from the one presented in the text. While that model included a full set of demographics and other control variables, interactions that let our main effects vary over political interest, random effects to deal with heterogeneity across choices, and fixed effects to deal with unmeasured effects, the specification below has none of this. It is a simple multinomial logit with the minimum set of variables and interactions necessary to capture the main hypotheses we proposed. In a sense, all the possible alternative models we could specify would fall between this one and the one in the text, in terms of complexity and (we hope) the correctness or incorrectness of the specification.

Thus, it is reassuring then that this very simple model gives the same substantive conclusions as the one reported in the text. This is apparent from Figure A4.1, which can be compared directly to Figure 2 in the text (but obviously not from comparing the coefficients in Table A4.1 and A2.3, since these *must* be different by construction). This gives us a great deal of confidence that the relationships we have identified are strongly "in the data" and not a product of specification decisions.

Figure A4.1 Simple Model: Conditional Effect of Party Position over Party Unity Score

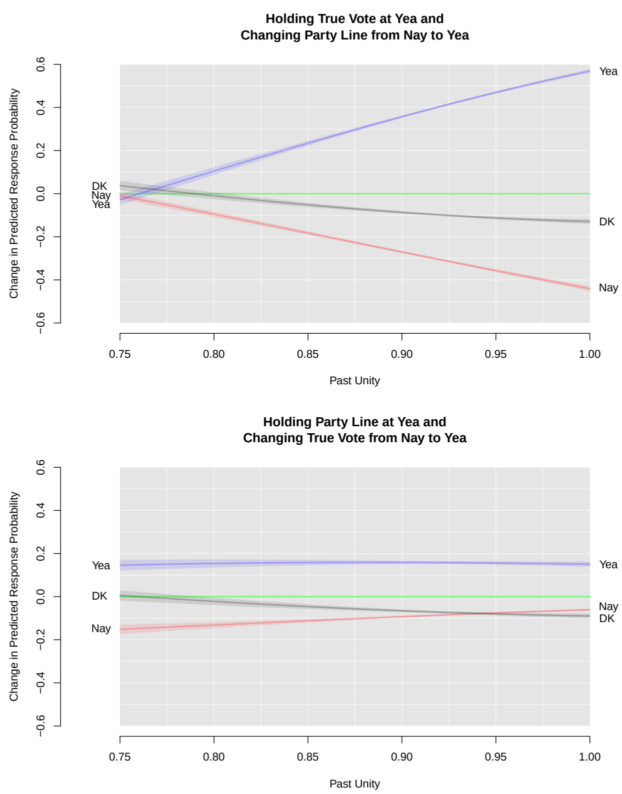
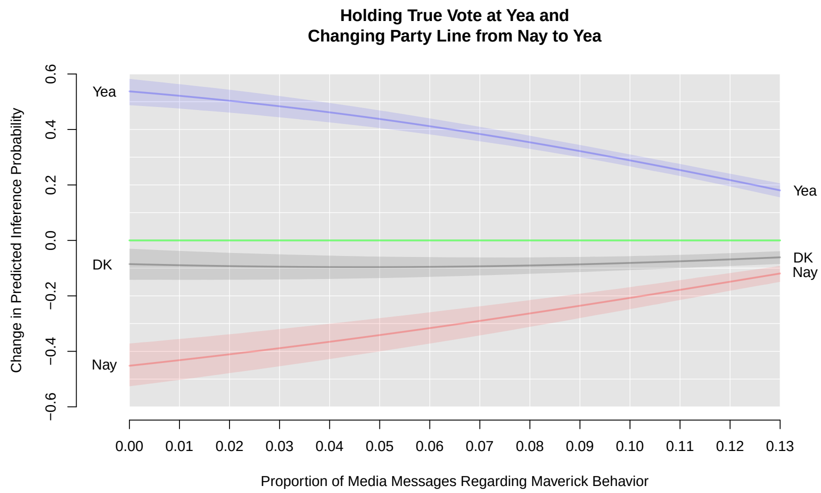


Figure A4.2: **Media Model**. Conditional Effect of Party Position over Proportion of Maverick Messages in the Media. Note that the directionality of the media message variable is the opposite of the party unity variable.



Measuring the media environment directly

In the text, we argued that the media's role in defining informational environments is to convert real congressional voting behaviors into narratives about these senators that condition how constituents perceive their senators and thus how often constituents "choose" to apply the *partisanship heuristic*. In making this argument, we provided evidence that the proportion of media messages referencing "maverick" (or contra-partisan) behaviors is significantly correlated to the real voting record of the senators in our sample. Consequently, it follows that we should get similar substantive results from a model in which we substitute our historical party unity score with our variable measuring the partisan disloyalty of the media message about the senator. In this section then, we replicate our main model for the 51 senators serving in the five sessions leading up to the 2006 elections, the same senators included in the analysis of media messaging included in the text. In this replication (on a smaller sample), we replace the senators' previous party unity score with the proportion of media messages referencing maverick behaviors over the past ten years — the same measure used in Figure 1 in the text (all other variables remain unchanged less the freshman indicator and interactions which are no longer necessary). The expectation is that voters' propensity to apply the *partisanship heuristic* will decrease as the proportion of maverick messages in the media's coverage of their senator increases and that this relationship will be conditioned by political interest just as before. We present the substantive effects of the relationship in Figure A4.2 below, a replication Figure 2 in the text. The corresponding coefficients are presented in table A4.2. The results confirm our expectations.

Partisan matching vs. partisan loyalty

In the text, we raised the possibility that voters key on partisan matching (between senators and state voter majorities) rather than their senator's historical party loyalty (or the media message stemming from it) to condition their use of the *partisanship heuristic*. As we explained, it could be that voters in strongly Republican states recognize that a Democratic senator in their state (a "mismatched" senator) will tend to vote against the Democratic leadership in Congress and so use this recognition, rather than party unity scores (as they shape the media environment), to condition their beliefs. In this case, the empirical implications of our explanation and the partisan matching hypothesis are the same — mismatched senators will tend to have low unity scores and voters will report (under both explanations) that mismatched senator are less loyal partisans.

In contrast, the two explanations suggest different conclusions for the alternative case in which well-matched senators are nonetheless disloyal to their party (e.g., John McCain — a Republican maverick in a Republican state). In this case, our explanation suggests that voters will recognize this disloyalty; however, the partisan matching hypothesis implies they will not since the senator is appropriately matched to his or her state majority. Likewise, while our explanation makes clear predictions in all states, the alternative fails to tell us what voters in swing states should believe about their senators (since it is unclear if they are matched or not). We can begin to access the evidence for these kinds of cases by looking more closely at the cases presented in Table 1 in the text. We see, for example, that in Arizona (a Republican majority state in this period), voters beliefs about the partisan loyalty of Senator Kyl were quite different than those of John McCain — even though they were both Republicans in a Republican state. Further, the differences match closely the differences in the senators' relative party unity scores. The California case tells the same story for two Democratic senators.

We can also examine this issue more generally. Specifically, since we want to test the partisan matching hypotheses against our historical party unity hypothesis, we estimated an alternative specification of our model that included not only historical party unity (and appropriate interactions) but also a measure of the extent to which a senator matches the partisan majority in his or her state (the share of the 2004 two-party presidential vote that a given senator's party won in the state) along with all the relevant interactions for this variable.[5] If voters are using partisan matching instead of historical party unity (or, more precisely, the media environment shaped by this record), we expect this new variable (along with its appropriate interactions) to supersede party unity as the best contextual predictor of voters' beliefs about senatorial votes.[6] Specifically, we would expect the two highlighted coefficients in Table A4.3 to be positive and negative respectively (as they are for the same interaction with party unity) — they are not. This result is consistent with the data we saw in Table 1 in the text, which illustrated just this effect: once we account for party unity scores, partisan matching provides no further guide to voters' beliefs about senatorial voting behavior.

In addition to this test of the two hypotheses, we also note that the explanations make different predictions about how individuals should predict the votes of freshman senators. In our explanation, there is no information on these senators' past votes and so voters go to their default assumption and treat them as party loyalists. In the partisan matching hypothesis, if the freshman senator is mismatched to the partisan majority in the state, voters should assume he or she will be a maverick. Unfortunately, in our data we do not have any clearly mismatched senators elected in 2004 with which to test this proposition (so we leave a more rigorous test to future work), however, given that the partisan match variable does not sap predictive power form the freshman indicator (and its interactions), these data suggest that the partisan matching explanation offers a poor fit for

[5]This measure (like party unity scores) will be smaller for mismatched senators.

[6]Because the point of this alternative specification (unlike the others presented so far) is to test between competing explanations, we needed to include both party unity and partisan matching variables (and all their interactions) in the model. Given the large number of interactions in the full model (as well as the other complications this model includes), we compare these hypotheses using the simpler specification introduced in the first part of this section on robustness.

freshmen as well as more senior senators.

Comparing samples

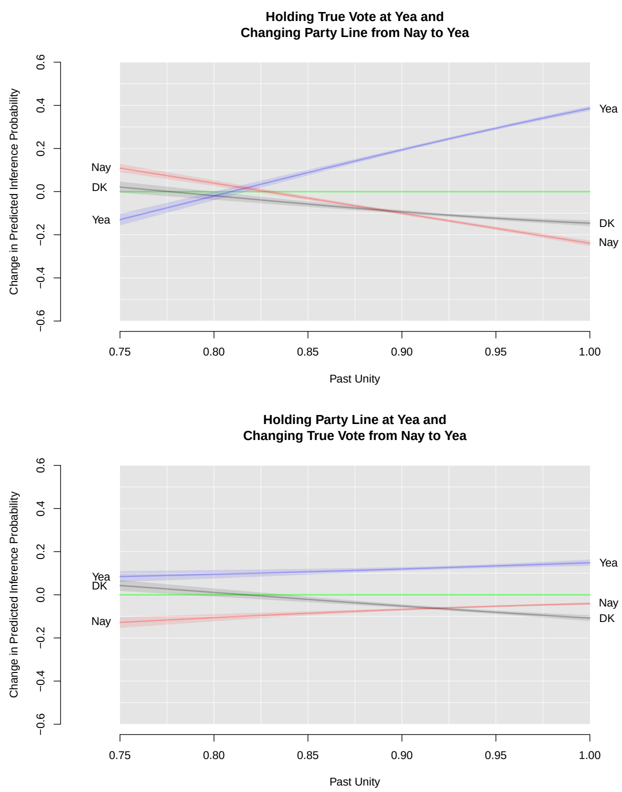
As discussed in the text, the results presented so far are based on a sample of respondents who have the political information necessary to apply the *partisanship heuristic* correctly if they "choose" to (i.e., they know their senator's party affiliation and the general relative ideological positions of the parties). In this section, we briefly discuss differences in the findings when we instead use the full sample of respondents. As noted in the main text, we analyze the full sample in two different ways, though there is very little difference between the results recovered from these different approaches and neither conflict with the substantive conclusion presented in the main text. First, we simply that all voters possess the informational inputs necessary to apply the *partisanship heuristic*; i.e., we assume all voters know the partisanship of their senator and know the position that party took on all roll call votes — the standard assumptions of previous work in this literature (Dancey and Sheagley 2013). Second, we conform the party line vote to reflect the perceptions of our respondents. This means that if a voter believes that her senator is a Democrat and knows that Democrats are to the left of Republicans, then we assign the "left" or true Democratic party position as the party line for the respondent-senator pair. If, however, a respondent believes his senator is a Democrat and also believes that Democrats are to the *left* of Republicans, then we assign the "right" or true Republican party position as the party line for the respondent-senator pair. Using this approach, we estimate models where we discard all observations for voters who respond "don't know" to the question of their senator's partisanship and one where we assign as party at random to those who give a "don't know" response. There is no substantive difference between model results and the graphics we display here are calculated from estimates using all respondents.

The short answer is that all of the relationships remain directionally consistent in the full sample. That is, all of the evidence we reported, the support for our main hypothesis (i.e., the ecologically rational application of the *partisanship heuristic*), the conditioning effect of political interest, and the treatment of freshman senators, remains statistically and substantively robust. The main difference is that the effects of political interest are exaggerated in the full sample. This makes perfect sense, since we are drastically expanding the variation on this variable when we use the full sample. After all, those without the requisite informational inputs to apply the *partisanship heuristic* tend to come from the lower interest categories.

Despite the broad similarity of the results with the full sample, there is one substantive difference in the results — a difference that we think illustrates the importance of studying the use of heuristics among those individuals with the informational prerequisites to use them. Specifically, recall that in Figures 3 and 4 in the text we found that high interest voters were significantly less likely to apply the *partisanship heuristic* than low interest voters in the context where it was least effective (when maverick senators vote against their party). This is an important substantive conclusion since it implies that there is no penalty to greater political interest — that is, though high interest voters in general use the *partisanship heuristic* more than low interest voters, they do not use it more often in situations in which it is inappropriate.

When we move to the full sample, however, we get a slightly different result. In the full sample the results suggest that high interest voters are more likely to apply the *partisanship heuristic* in all contexts, even where it is least effective and leads to incorrect inference — this is particularly evident in Figure A4.4. Thus, the full sample model weakly implies an interest penalty: a situation in which more interested voters should be at a systematic disadvantage in comparison to their less interested counterparts — a conclusion that Dancey and Sheagley (2013) recently came to. Which result is correct? In our view it seems clear that voters who do not possess the informational prerequisites to apply the *partisanship heuristic* (do not know the party of their senator or the positions the parties took on the issue), cannot apply the heuristic. Thus, excluding them from an analysis designed to examine the conditions under which voters choose to apply it is appropriate (so the results based on this sample are those that we care about). Of course, that position is to some extent philosophical — resulting from our understanding of heuristics as both the rule that voters apply and the information that they need to apply it, so we are not inclined to criticize others whose definitions and purposes are different from ours. However, it is important simply to understand that one's position on this issue can have (as it does here) important substantive implications. Indeed, the finding that high interest voters use heuristics in inappropriate contexts is something Dancey and Sheagley (2013) emphasize as an important substantive conclusion from their study.

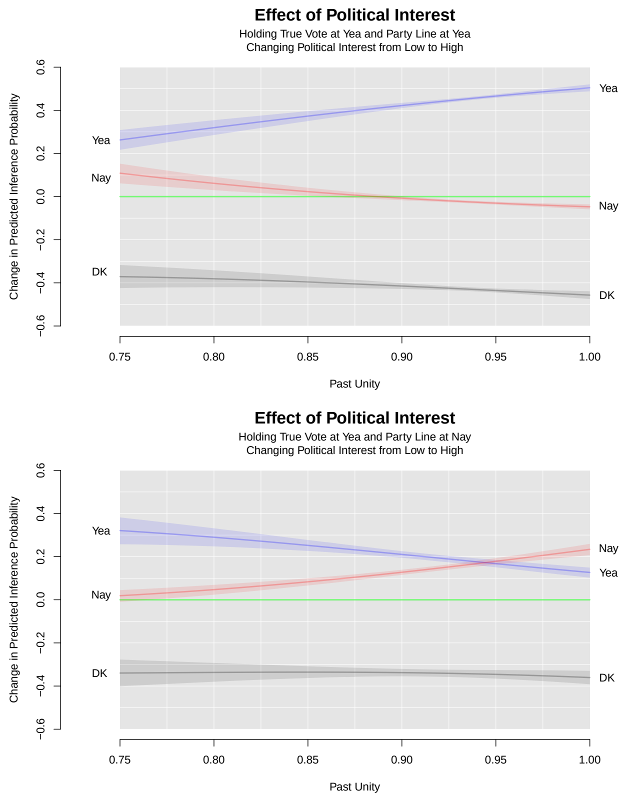
Figure A4.3 Full sample model: Conditional Effect of Party Position over Party Unity Score by Interest Level



Other variations in model specification

In addition to the analyses above, we ran a variety of alternative specifications of fixed and random effects, as well as various combinations of the covariates included in the models. These include models with fixed effects for senators and random effects for responses (i.e., senator-issue-respondents), models with fixed effects for senators and issues (and no random effects), models with fixed effects for senator-issues, and different models with random effects for senators, issues, and senator-issues, respectively (without response level random effects). All of these analyses are available from the

Figure A4.4 Full sample model: Conditional Effect of Interest on Heuristic Use over Party Unity Score by Interest Level



authors but the bottom line is that none of it matters at all for the conclusions we have presented here.

Section A5: Analysis of media message about senatorial loyalty

Construction of the Measure

In this section we provide the detailed search terms for the measure of media messages about partisan loyalty. Our measure calculates the ratio $\frac{\text{\# of messages including senator AND ``maverick'' language}}{\text{\# of messages including senator}}$ by searching all U.S. newspapers and (transcripts of) news broadcasts covered in the Factiva database for January 3, 1997 - January 3 2007. The broad search (denominator) was simply a vector of search terms including different ways the senator could be referenced. For example, our search string for Sen. Snowe of Maine was: ("Olympia Snowe, senator" or "Olympia Snowe senator" or "Olympia Snowe (R)" or "Senator Olympia Snowe" or "Sen. Olympia Snowe" or "Sen Olympia Snowe" or "Sen Snowe" or "Senator Snowe" or "Sen. Snowe"). From this set of articles, we then identified any that contained "maverick" language (this number is the numerator in our ratio). After reviewing a larger number of randomly selected articles, we identified the following terms and phrases as ones indicating the story was describing the senator, at least to some degree, as a "maverick": "against the party," "against her party," "against his party," "contrary to the party," "contrary to her party," "contrary to his party," "joined the opposition," "buck the party," "buck her party," "buck his party," "maverick," "mavericks," "reach across the aisle," "reached across the aisle," "reaching across the aisle," "reaches across the aisle," "rogue," "rogues," "dissenter," "moderate," "rare bird," and "loner." Finally, we experimented with different subsets of these terms (excluding, for example, "moderate") as well as with more subtle searches requiring these words to be proximate to the senator's name. None of these experiments resulted in substantially different rankings of senators - that is, while the these changes shifted the number of stories returned in the numerator they tended to do so proportionately across senators, so that all the ratios would shift up and down but he relative ratios did not change much — the same mavericks were identified by different measures.

Statistical analysis behind the relationship in Table 1

In this section we provide the details of the regression analysis supporting the conclusions illustrated in Table 1. Given that we only have 51 data points in the analysis, we want to be certain that the statistically robust relationship between party unity as expressed in legislative votes and the content of media messaging is not driven by outliers. Thus, in Table A5.1 below, we present the results from a non-parametric bootstrapping exercise. In this exercise, we randomly sample (with replacement) 51 observations from the true data, regress the ratio of media messages mentioning maverick behavior to all media messages regarding the senator on their party unity score and then draw ten simulated parameters from the posterior. This is repeated 5,000 times and the figures reported in Table A5.1 are the means and standard deviations of those 50,000 parameter draws. As the table shows, the relationship is quite robust.

A6: Knowledge of Party general Liberal-Conservative Positions predicts Knowledge of Party Positions on Specific Issues

The text refers to our statistical analysis of the relationship between knowledge of the general liberal-conservative ideologies of the parties and knowledge of party positions on specific issues. This analysis, which supports the importance of this relationship, undergirds our assumption that respondents in our sample who could put the parties in the correct order on a general liberal-conservative dimension, likely knew the parties positions on the kinds of salient issues asked about in the survey.

The *Stata* do files are available from the authors and the data is available for download from the Pew research center (here). These files simply produce a series of logistic regressions that model the impact of knowing the parties' relative positions on the liberal conservative scale on the probability of correctly identifying which party was most likely to support each of seven different issue positions included in the pew survey. These analyses controlled for education, age, and gender and, using simulated changes in probabilities of correctly identifying party issue positions when moving from not knowing to knowing the parties' relative liberal-conservative ideologies, showed that the changes in probabilities where 30% for five of the issues (abortion, gay rights, arctic drilling, size of government, health care reform) and 15% for two of the issues (defense spending positions and immigration positions). Because this survey was administered approximately 7 years after years after the 2006 CCES and and we did not constrain our sample in the same fashion for these analyses, these figures are obviously not directly comparable to the sample we test our hypothesis, rather, is only meant to illustrative how knowledge of general liberal-conservative positions should enhance the probability of knowing more specific issue positions.

Table A2.1: Conceptual and Operational Variables

	Dependent Variable: How do you think Senator X voted on Issue Y?		
	Yea	Nay	Don't Know
Senator's True Vote on the Bill (True Vote)			
Indicator for True Vote Yea			Baseline
Indicator for True Vote Nay			Baseline
Indicator for True Vote Abstain	Baseline	Baseline	Baseline
Senator's Party's Position on the Bill (Party Position)			
Indicator for Party Position Yea			Baseline
Indicator for Party Position Nay	Baseline	Baseline	Baseline
Senator's Historical Party Unity (Party Unity)			
Party Unity Score (range = 0 - 1, mean = 0.827)			Baseline
Was the Senator a Freshman? (Freshman)			
Indicator for Freshman Senator (10 freshman out of 99 senators))			Baseline
Respondent's Level of Political Interest (Political Interest)			
Party Unity Score (range = 1 - 3, mean = 2.71)			Baseline
Interaction: Senator's True Vote and his or her Historical Party Unity			
Indicator for True Vote Yea * Party Unity Score			Baseline
Indicator for True Vote Nay * Party Unity Score			Baseline
Indicator for True Vote Abstain * Party Unity Score	Baseline	Baseline	Baseline
Interaction: Senator's True Vote and whether he or she was a Freshman			
Indicator for True Vote Yea * Indicator for Freshman			Baseline
Indicator for True Vote Nay * Indicator for Freshman			Baseline
Indicator for True Vote Abstain * Indicator for Freshman	Baseline	Baseline	Baseline
Interaction: Senators Party's Position on the Bill and his or her Historical Party Unity			
Indicator for Party Position Yea * Party Unity Score			Baseline
Indicator for Party Position Nay * Party Unity Score	Baseline	Baseline	Baseline
Interaction: Senators Party's Position on the Bill and whether he or she was a Freshman			
Indicator for Party Position Yea * Indicator for Freshman			Baseline
Indicator for Party Position Nay * Indicator for Freshman	Baseline	Baseline	Baseline
Interaction: Senator's Historical Party Unity and Respondent's Level of Political Interest			
Party Unity Score * Political Interest Score			Baseline
Interaction: whether the Senator was a Freshman and Respondent's Level of Political Interest			
Indicator for Freshman * Political Interest Score			Baseline
Interaction: Senator's True Vote and Respondent's Level of Political Interest			
Indicator for True Vote Yea * Political Interest Score			Baseline
Indicator for True Vote Nay * Political Interest Score			Baseline
Indicator for True Vote Abstain * Political Interest Score	Baseline	Baseline	Baseline
Three way Interaction: Senator's True Vote, Historical Party Unity, and Respondent's Level of Political Interest			
Indicator for True Vote Yea * Party Unity Score * Political Interest Score			Baseline
Indicator for True Vote Nay * Party Unity Score * Political Interest Score			Baseline
Indicator for True Vote Abstain * Party Unity Score * Political Interest Score	Baseline	Baseline	Baseline
Three way Interaction: Senator's True Vote, Freshman, and Respondent's Level of Political Interest			
Indicator for True Vote Yea * Indicator for Freshman * Political Interest Score			Baseline
Indicator for True Vote Nay * Indicator for Freshman * Political Interest Score			Baseline
Indicator for True Vote Abstain * Indicator for Freshman * Political Interest Score	Baseline	Baseline	Baseline
Three way Interaction: Senator's Party's Position, Historical Party Unity, and Respondent's Level of Political Interest			
Indicator for Party Position Yea * Party Unity Score * Political Interest Score			Baseline
Indicator for Party Position Nay * Party Unity Score * Political Interest Score	Baseline	Baseline	Baseline
Three way Interaction: Senator's Party's Position, Freshman, and Respondent's Level of Political Interest			
Indicator for Party Position Yea * Indicator for Freshman * Political Interest Score			Baseline
Indicator for Party Position Nay * Indicator for Freshman * Political Interest Score	Baseline	Baseline	Baseline
Respondent's Preference for How to vote on the Bill			
Indicator for Respondent's Yea Preference			Baseline
Indicator for Respondent's Nay Preference			Baseline
Indicator for Respondent's Don't Know Response	Baseline	Baseline	Baseline
Does the Respondent have the same Party Affiliation as the Senator? (*Co-partisans*)			
Indicator for Co-partisans			Baseline
Indicator for Party Position Nay	Baseline	Baseline	Baseline
Interaction: Senator's True Vote on the Bill and whether the Respondent has the same Party Affiliation as the Senator			
Indicator for True Vote Yea * Co-partisans			Baseline
Indicator for True Vote Nay * Co-partisans			Baseline
Indicator for True Vote Abstain * Co-partisans	Baseline	Baseline	Baseline
Interaction: Senator's Party's Position on the Bill and whether the Respondent has the same Party Affiliation as the Senator			
Indicator for Party Position Yea * Indicator for Co-partisans			Baseline
Indicator for Party Position Nay * Indicator for Co-partisans	Baseline	Baseline	Baseline
Interaction: Respondent's Preference and whether the Respondent has the same Party Affiliation as the Senator			
Indicator for Respondent's Yea Preference * Indicator for Co-partisans			Baseline
Indicator for Respondent's Nay Preference * Indicator for Co-partisans			Baseline
Indicator for Respondent's Don't Know Response * Indicator for Co-partisans	Baseline	Baseline	Baseline

Table A2.2: The Grouping Structure of the Data

			Issues CROSSED with States		Respondents CROSSED with Senators		
	Alternatives NESTED within choices			Senators NESTED within states (thus, also crossed with issues)			
Row	**Choice**	**Alternative**	**Issue**	**State**	**Senator**	**Respondent**	
1	1	Yea	Abortion	Alabama	Shelby	A	
2	1	Nay	Abortion	Alabama	Shelby	A	
3	1	DK	Abortion	Alabama	Shelby	A	
4	2	Yea	Abortion	Alabama	Sessions	A	
5	2	Nay	Abortion	Alabama	Sessions	A	
6	2	DK	Abortion	Alabama	Sessions	A	
7	3	Yea	Abortion	Colorado	Allard	B	
8	3	Nay	Abortion	Colorado	Allard	B	
9	3	DK	Abortion	Colorado	Allard	B	
10	4	Yea	Abortion	Colorado	Salazar	B	
11	4	Nay	Abortion	Colorado	Salazar	B	
12	4	DK	Abortion	Colorado	Salazar	B	
13	5	Yea	Trade	Alabama	Shelby	A	
14	5	Nay	Trade	Alabama	Shelby	A	
15	5	DK	Trade	Alabama	Shelby	A	
16	6	Yea	Trade	Alabama	Sessions	A	
17	6	Nay	Trade	Alabama	Sessions	A	
18	6	DK	Trade	Alabama	Sessions	A	
19	7	Yea	Trade	Colorado	Allard	B	
20	7	Nay	Trade	Colorado	Allard	B	
21	7	DK	Trade	Colorado	Allard	B	
22	8	Yea	Trade	Colorado	Salazar	B	
23	8	Nay	Trade	Colorado	Salazar	B	
24	8	DK	Trade	Colorado	Salazar	B	

Table A2.3 **Main Model**. Hierarchical Multinomial Logit Estimates: Baseline Response Category is “Don’t Know” and Baseline Issue Category is CAFTA.

	Yea inference						Nay inference		
Variable	Parameter	(se)	$p > \|z\|$				Parameter	(se)	$p > \|z\|$
True Vote Yea	−4.197	(7.132)	0.556				−17.572	(8.323)	0.035
True Vote Nay	−4.647	(7.205)	0.519				−16.539	(8.297)	0.046
Party Position Yea	−3.450	(1.964)	0.079				0.588	(2.316)	0.800
Party Unity Score	−5.773	(7.845)	0.462				−15.841	(8.968)	0.077
Freshman	−4.335	(7.183)	0.546				−14.015	(8.283)	0.091
Political Interest	0.201	(2.647)	0.939				−5.629	(3.015)	0.062
True Vote Yea * Party Unity Score	4.665	(7.806)	0.550				19.538	(9.030)	0.030
True Vote Yea * Freshman	3.716	(7.138)	0.603				17.141	(8.333)	0.040
True Vote Nay * Party Unity Score	5.535	(7.880)	0.482				18.019	(8.992)	0.045
True Vote Nay * Freshman	4.248	(7.216)	0.556				16.360	(8.305)	0.049
Party Position Yea * Party Unity Score	4.659	(2.136)	0.029				−1.867	(2.507)	0.457
Party Position Yea * Freshman	3.895	(1.992)	0.051				−1.562	(2.350)	0.506
Party Unity Score * Political Interest	0.330	(2.901)	0.910				6.836	(3.268)	0.036
Freshman * Political Interest	0.035	(2.649)	0.990				6.046	(3.017)	0.045
True Vote Yea * Political Interest	1.289	(2.631)	0.624				5.682	(3.032)	0.061
True Vote Nay * Political Interest	1.981	(2.659)	0.456				5.786	(3.023)	0.056
Party Position Yea * Political Interest	−0.998	(0.729)	0.171				2.151	(0.856)	0.012
True Vote Yea * Party Unity Score * Political Interest	−1.286	(2.887)	0.656				−6.396	(3.291)	0.052
True Vote Yea * Freshman * Political Interest	−1.067	(2.633)	0.685				−5.658	(3.036)	0.062
True Vote Nay * Party Unity Score * Political Interest	−2.362	(2.915)	0.418				−6.235	(3.277)	0.057
True Vote Nay * Freshman * Political Interest	−2.071	(2.663)	0.437				−5.610	(3.026)	0.064
Party Position Yea * Party Unity Score * Political Interest	1.243	(0.792)	0.117				−2.491	(0.927)	0.007
Party Position Yea * Freshman * Political Interest	1.298	(0.739)	0.079				−2.328	(0.868)	0.007
Respondent Yea Prefernce	0.864	(0.031)	0.000				1.459	(0.036)	0.000
Respondent Nay Prefernce	1.335	(0.032)	0.000				1.069	(0.037)	0.000
Co-partisans	−0.448	(0.095)	0.000				−0.887	(0.114)	0.000
True Vote Yea * Co-partisans	−0.135	(0.079)	0.087				0.293	(0.104)	0.005
True Vote Nay * Co-partisans	−0.325	(0.085)	0.000				0.251	(0.105)	0.016
Party Position Yea * Co-partisans	−0.515	(0.040)	0.000				0.776	(0.046)	0.000
Respondent Yea Prefernce * Co-partisans	1.292	(0.052)	0.000				−0.659	(0.057)	0.000
Respondent Nay Prefernce * Co-partisans	−0.025	(0.054)	0.644				0.791	(0.056)	0.000
Female	−0.333	(0.014)	0.000				−0.427	(0.015)	0.000
Race	0.009	(0.017)	0.611				−0.034	(0.019)	0.066
Income	0.020	(0.002)	0.000				0.018	(0.002)	0.000
Education	0.077	(0.005)	0.000				0.070	(0.006)	0.000
Issue: Partial Birth Abortion Ban	0.751	(0.027)	0.000				1.026	(0.031)	0.000
Issue: Capital Gains Tax Cut Extension	0.535	(0.026)	0.000				0.900	(0.029)	0.000
Issue: Immigration Reform	0.485	(0.025)	0.000				0.549	(0.028)	0.000
Issue: Iraq Withdrawal	0.704	(0.028)	0.000				1.332	(0.031)	0.000
Issue: Stem Cell Research	0.695	(0.026)	0.000				1.032	(0.030)	0.000
Issue: Minimum Wage Increase	0.808	(0.026)	0.000				0.640	(0.030)	0.000
Intercept	1.532	(7.175)	0.831				11.062	(8.276)	0.181
Random Coefficients Covariance Structure:									
Yea				0.186	(0.154)	0.229			
Nay				−0.030	(0.066)	0.652			
Yea-Nay				0.187	(0.154)	0.226			
N(Issues)					7				
N(Senators)					99				
N(Respondents)					13369				
N(Choices)					172725				
N(Total)					518175				
LogLikelihood					-139757.93				
Predictive accuracy: All responses					0.649				
Predictive accuracy: Yea/Nay responses					0.771				

Table A4.1: **Simple Model**. Multinomial Logit Estimates: Baseline Response Category is "Don't Know," baseline senator vote is abstention, baseline party position is "Nay," baseline respondent preference is "Don't Know."

	Yea inference			Nay inference		
Variable	Parameter	(se)	$p > \|z\|$	Parameter	(se)	$p > \|z\|$
True Vote Yea	0.397	(1.037)	0.702	0.359	(1.114)	0.747
True Vote Nay	0.834	(1.051)	0.428	1.610	(1.107)	0.146
Party Position Yea	−6.318	(0.295)	0.000	4.877	(0.344)	0.000
Party Unity Score	−3.877	(1.158)	0.001	4.511	(1.192)	0.000
Freshman	−3.117	(1.044)	0.003	4.331	(1.104)	0.000
True Vote Yea * Party Unity Score	0.008	(1.153)	0.994	−0.577	(1.206)	0.632
True Vote Yea * Freshman	−0.468	(1.038)	0.652	−0.862	(1.116)	0.440
True Vote Nay * Party Unity Score	−1.036	(1.167)	0.375	−1.368	(1.197)	0.253
True Vote Nay * Freshman	−1.702	(1.052)	0.106	−1.446	(1.108)	0.192
Party Position Yea * Party Unity Score	8.199	(0.320)	0.000	−6.730	(0.372)	0.000
Party Position Yea * Freshman	7.555	(0.298)	0.000	−6.370	(0.347)	0.000
Respondent Yea Prefernce	1.492	(0.017)	0.000	1.654	(0.019)	0.000
Respondent Nay Prefernce	1.538	(0.017)	0.000	1.545	(0.020)	0.000
Intercept	1.474	(1.043)	0.158	−5.469	(1.104)	0.000
N(Choices)			301294			
N(Total)			903882			
LogLikelihood			-259363.100			

Table A4.2: **Media Message Model**. Hierarchical Multinomial Logit Estimates: Baseline Response Category is "Don't Know" and Baseline Issue Category is CAFTA.

	Yea inference			Nay inference		
Variable	Parameter	(se)	$p > \|z\|$	Parameter	(se)	$p > \|z\|$
True Vote Yea	0.383	(0.735)	0.602	2.177	(1.003)	0.030
True Vote Nay	0.374	(0.814)	0.646	2.141	(1.011)	0.034
Party Position Yea	0.656	(0.405)	0.105	−1.588	(0.466)	0.001
Maverick Messages	2.368	(9.146)	0.796	20.821	(11.337)	0.066
Political Interest	0.109	(0.305)	0.722	1.516	(0.375)	0.000
True Vote Yea * Maverick Messages	−4.784	(8.479)	0.573	−21.207	(11.272)	0.060
True Vote Nay * Maverick Messages	−2.426	(9.471)	0.798	−24.866	(11.587)	0.032
Party Position Yea * Maverick Messages	1.661	(4.800)	0.729	8.383	(5.737)	0.144
Maverick Messages * Political Interest	3.351	(3.453)	0.332	−9.843	(4.255)	0.021
True Vote Yea * Political Interest	0.062	(0.286)	0.829	−0.974	(0.378)	0.010
True Vote Nay * Political Interest	−0.012	(0.313)	0.971	−0.952	(0.381)	0.012
Party Position Yea * Political Interest	0.520	(0.148)	0.000	−0.334	(0.170)	0.050
True Vote Yea * Maverick Messages * Political Interest	1.898	(3.217)	0.555	8.830	(4.229)	0.037
True Vote Nay * Maverick Messages * Political Interest	−0.642	(3.569)	0.857	12.285	(4.340)	0.005
Party Position Yea * Maverick Messages * Political Interest	−4.281	(1.758)	0.015	1.868	(2.103)	0.374
Respondent Yea Prefernce	0.794	(0.040)	0.000	1.397	(0.048)	0.000
Respondent Nay Prefernce	1.296	(0.040)	0.000	1.007	(0.050)	0.000
Co-partisans	−0.861	(0.170)	0.000	−0.923	(0.194)	0.000
True Vote Yea * Co-partisans	0.063	(0.152)	0.679	0.334	(0.182)	0.066
True Vote Nay * Co-partisans	0.019	(0.160)	0.906	0.244	(0.183)	0.183
Party Position Yea * Co-partisans	−0.395	(0.055)	0.000	0.686	(0.064)	0.000
Respondent Yea Prefernce * Co-partisans	1.329	(0.072)	0.000	−0.601	(0.079)	0.000
Respondent Nay Prefernce * Co-partisans	0.068	(0.074)	0.358	0.817	(0.077)	0.000
Female	−0.309	(0.019)	0.000	−0.415	(0.021)	0.000
race	−0.003	(0.025)	0.896	−0.066	(0.026)	0.011
Income	0.023	(0.003)	0.000	0.017	(0.003)	0.000
Education	0.062	(0.008)	0.000	0.060	(0.008)	0.000
Issue: Partial Birth Abortion Ban	0.675	(0.035)	0.000	1.123	(0.039)	0.000
Issue: Capital Gains Tax Cut Extension	0.436	(0.036)	0.000	0.922	(0.038)	0.000
Issue: Immigration Reform	0.378	(0.034)	0.000	0.618	(0.039)	0.000
Issue: Iraq Withdrawal	0.711	(0.037)	0.000	1.357	(0.040)	0.000
Issue: Stem Cell Research	0.705	(0.035)	0.000	1.155	(0.040)	0.000
Issue: Minimum Wage Increase	0.677	(0.035)	0.000	0.757	(0.040)	0.000
Intercept	−3.546	(0.794)	0.000	−5.210	(0.997)	0.000
Inference Level Random Intercept	0.056	(0.163)	0.731	0.048	(0.177)	0.786
N(Issues)					7	
N(Senators)					51	
N(Respondents)					8781	
N(Choices)					85617	
N(Total)					256851	
LogLikelihood					-69043.098	
Predictive accuracy: All responses					0.649	
Predictive accuracy: Yea/Nay responses					0.767	

Table A4.3: **Partisan Match Model**. Multinomial Logit Estimates: Baseline Response Category is "Don't Know," baseline senator vote is abstention, baseline party position is "Nay," baseline respondent preference is "Don't Know."

	Yea inference			Nay inference		
Variable	Parameter	(se)	$p > \|z\|$	Parameter	(se)	$p > \|z\|$
True Vote Yea	0.709	(1.020)	0.487	0.412	(1.155)	0.721
True Vote Nay	0.612	(1.038)	0.556	1.346	(1.151)	0.242
Party Position Yea	−7.115	(0.305)	0.000	4.745	(0.359)	0.000
Party Unity Score	−8.083	(1.188)	0.000	3.013	(1.402)	0.032
Freshman	−7.169	(1.081)	0.000	2.887	(1.302)	0.027
Partisan Match	6.894	(0.685)	0.000	2.364	(0.813)	0.004
True Vote Yea * Party Unity Score	2.172	(1.167)	0.063	0.260	(1.406)	0.853
True Vote Yea * Freshman	1.711	(1.060)	0.107	−0.026	(1.306)	0.984
True Vote Nay * Party Unity Score	2.750	(1.204)	0.022	0.371	(1.408)	0.792
True Vote Nay * Freshman	1.961	(1.097)	0.074	0.227	(1.308)	0.862
Party Position Yea * Party Unity Score	10.536	(0.394)	0.000	−6.369	(0.471)	0.000
Party Position Yea * Freshman	9.704	(0.368)	0.000	−6.045	(0.441)	0.000
True Yea * Partisan Match	−4.575	(0.664)	0.000	−1.640	(0.819)	0.045
True Nay * Partisan Match	−6.399	(0.698)	0.000	−2.611	(0.821)	0.001
Party Position Yea * Partisan Match	−2.562	(0.260)	0.000	−0.381	(0.313)	0.223
Respondent Yea Prefernce	1.490	(0.017)	0.000	1.654	(0.019)	0.000
Respondent Nay Prefernce	1.534	(0.017)	0.000	1.547	(0.020)	0.000
Intercept	1.816	(1.027)	0.077	−5.297	(1.148)	0.000
N(Choices)			301294			
N(Total)			903882			
LogLikelihood			-259275.330			

Table A5.1: The effect of party unity scores on the proportion of media stories mentioning maverick behavior.

Covariate	Estimate
Partisan Unity Score	-0.270
	(0.109)
Intercept	0.311
	(0.100)
N	51
Mean AIC	-241.259
sd(AIC)	9.400