Online Appendix

Reassessing the Supreme Court: How Decisions & Negativity Bias Affect Legitimacy

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1 Panel Sample

We recruited participants using Amazon's Mechanical Turk (MTurk) and then directed them to the survey which we implemented online with Survey Gizmo. Samples recruited from the MTurk online crowdsourcing marketplace are becoming increasingly common in the social sciences (Berinsky, Huber and Lenz, 2012; Buhrmester, Kwang and Gosling, 2011). While MTurk samples have their limitations, papers using them have been published in the field's top journals (Huber, Hill and Lenz, 2012; Grimmer, Messing and Westwood, 2012; Arceneaux, 2012; Healy and Lenz, 2014; Dowling and Wichowsky, 2014; Christenson and Glick, 2015*a*,*b*). Indeed MTurk is an especially useful tool for implementing survey experiments and panel studies (like our study) which emphasize within subject changes rather than population estimates.

We recruited participants to the first wave of the panel in early June 2013 by posting a "HIT" (an open ad) on MTurk. In line with other MTurk recruiting, we offered $1 for a "15-18 minute survey of your views." Following Berinsky, Huber and Lenz (2012) we restricted the posting to MTurk users, over 18, with at least a 95% approval rating on their previous tasks, and to U.S. residents. Participants were recruited to subsequent waves based on completing each prior one. MTurk allows users to anonymously contact users by writing a code that includes a list of Amazon Turk ID numbers. Each Monday until the week when the decisions were actually released we sent such an email to those still in the panel inviting them to the next survey. The survey was private such that only those invited could find or access it.

We started with 844 participants and retained 487 through Wave 6. This 58% retention rate is impressive especially given the demands of the study. To make it through Wave 6, participants had to complete five surveys in a four week period and then continue participating with the final wave six weeks later. The biggest question with any MTurk sample concerns sample demographics and perhaps the biggest additional question relevant to a panel study concerns attrition. We address both using the information in Table A1 which summarizes our Wave 1 and Wave 6 demographics next to other surveys Berinsky, Huber and Lenz (see, e.g., 2012).

This table builds on prior work that has explored the natural questions that arise from a new electronic source for convenience samples. According to Berinsky, Huber and Lenz (2012), MTurk samples are more representative than other convenience samples (e.g., student samples) used in papers published in the *American Political Science Review*, *American Journal of Political Science*, and *Journal of Politics*. Berinsky et al. show that MTurk participants are younger and more liberal than the population as a whole. Importantly, they also show that MTurk survey takers are sometimes more similar to participants in nationally representative samples than are participants in the ANES panel study. For example, MTurk participants are less over-educated than those in the ANES-P and that their voting registration and participation rates are also more similar to the national samples than those in the ANES-P. All in all, they show that MTurk deviates in predictable ways and should never be mistaken for a national sample but that MTurk data are likely better than many assume they are and have significant value in studies that rely on within subject changes. "All told, these comparisons reinforce the conclusion that the MTurk sample does not perfectly match the demographic and attitudinal characteristics of the U.S. population but does not present a wildly distorted view of the U.S. population either. Statistically significant differences exist between the MTurk sample and the benchmark surveys, but these differences are substantively small. MTurk samples will often be more diverse than convenience samples and will always be more diverse than student samples" (Berinsky, Huber and Lenz, 2012).

Table A1: Sample Demographics and Comparison with Other Surveys

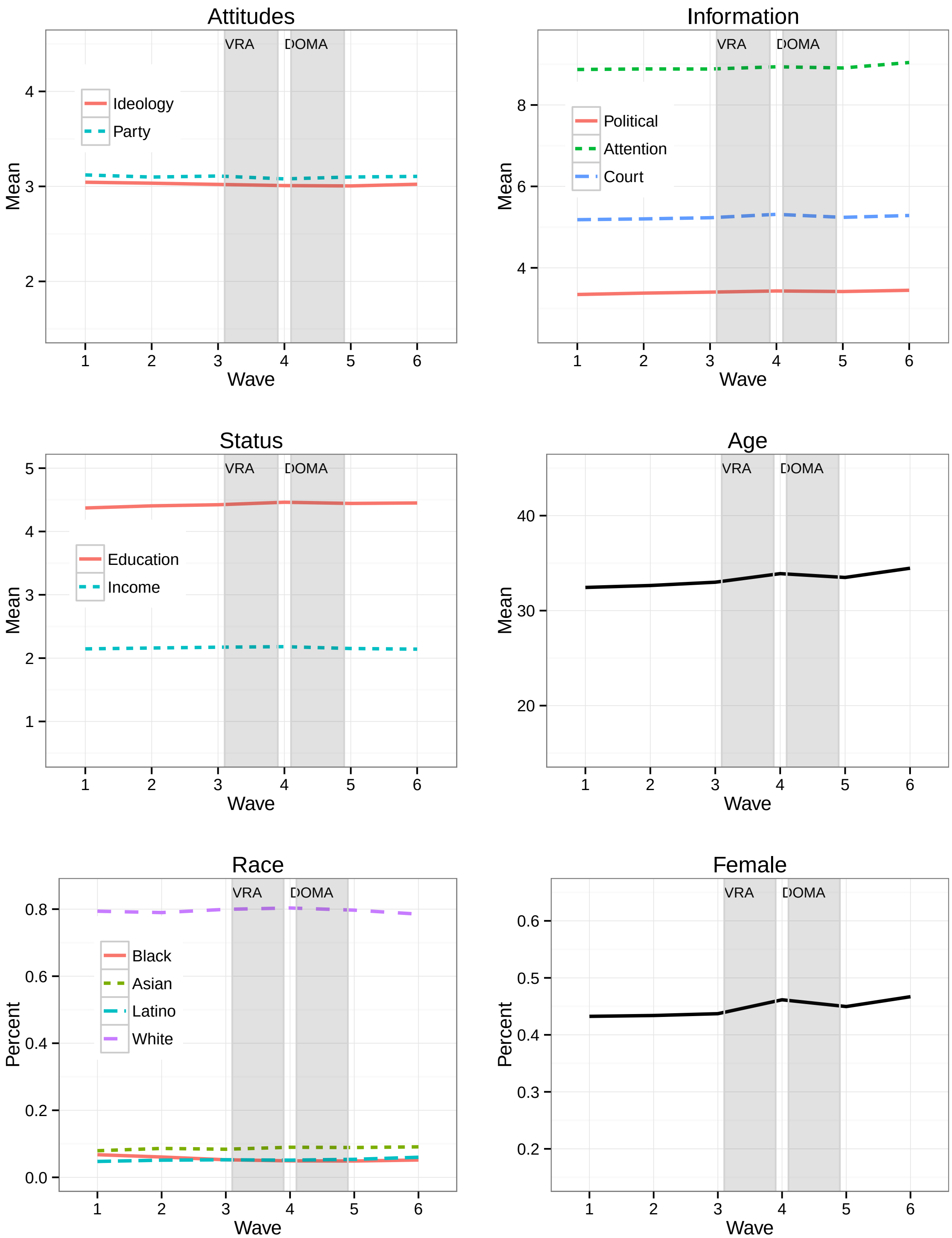
	Our Sample		**Internet Samples**		**Face to Face Samples**	
Variable	**Wave 1**	**Wave 6**	**BHL Turk**	**ANES-P 08-09**	**CPS 08**	**ANES 08**
% Female	43.2	47.0	60.1	57.6	51.7	55.0
% White	79.4	78.6	83.5	83.0	81.2	79.1
% Black	6.8	5.1	4.4	8.9	11.8	12.0
% Hispanic	4.8	6.0	6.7	5.0	13.7	9.1
Age (years)	32.4	34.4	32.3	49.7	46.0	46.6
Party ID (mean 7 pt.)	3.1	3.1	3.5	3.9		3.7
Income (median)	30-49K	30-49K	45K	67.5K	55K	55K

Traits for our sample from Wave 1 (N=844), Wave 6 (N=487) BHL Turk = Berinsky, Huber and Lenz (2012), ANES-P = American National Election Panel Study (Knowledge Networks), CPS = Current Population Survey, ANES = American National Election Study), CPS and ANES are weighted. Data from all columns other than Our Sample reproduced from Table 3 in Berinsky, Huber and Lenz (2012).

Like other MTurk samples, ours is not as representative as the field's best national probability samples but outperforms typical convenience samples. Table A1 mirrors the table in Berinsky, Huber and Lenz (2012) by comparing our population to their MTurk sample and to others including the 2008-2009 American National Election Panel Study (ANES-P) conducted by Knowledge Networks, and to two highly regarded, traditional, nationally representative samples, the 2008 Current Population Survey (CPS) and the 2008 ANES. Overall, our sample appears to closely mirror the population with a few expected deviations. Moreover, at least as important a consideration in a panel study, the panel attrition is not systematic with respect to demographics; our first and sixth waves have similar demographics and are especially similar in terms of the all important Party ID variable.

We further emphasize that *panel attrition is not systematic with respect to demographics, attitudes, political interest or information.* We demonstrate this across a wide range of variables with the graphs in Figure A1. Here we have plotted the mean values (for ordinal and continuous variables) and proportions (for the dummy variables) at each wave and connected them with a line. Non zero slopes would suggest that the composition of the sample at one wave differed systematically from the other wave on that variable. In contrast, a flat line would suggest that the samples did not change on that variable. Here we look at: political attitudes (strength of party identification and ideology), political information (including general political interest, attention to politics, and Court specific information), income, educational attainment, age, race and gender of the respondents. In all cases we find remarkably flat lines. The range of wave averages on partisanship ($[3.10,\ 3.12]$, seven point scale) and ideology ($[3.01,\ 3.04]$, seven point scale), along with interest in politics ($[2.91,\ 2.98]$, four point scale) and information about the Supreme Court ($[5.18, 5.31]$, seven point scale) were all extremely stable. The biggest changes, which are actually quite small, occur in terms of gender and age. As the panel progressed, the proportion of females in the panel moves up from 43.2% to 47% and the mean age of the respondent bumps up about 2 years. It appears that it is slightly easier to maintain older and female respondents. Overall, we are able to find little to no evidence that the panel sample changes in any systematic way as time goes on. Instead, respondents leave the sample in what appears to be a random manner. The respondents that stay in the panel are not more or less informed, interested, attentive, liberal, Democrat or white than those that depart.

Figure A1: Panel Attrition

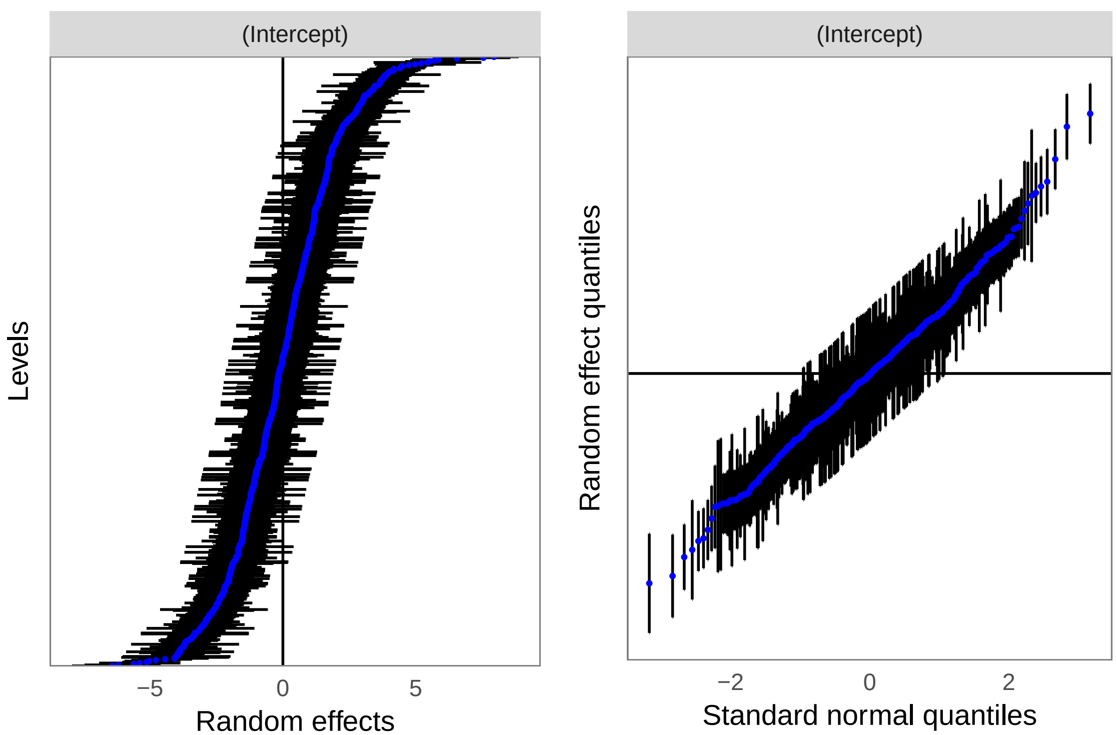


2 Linear Mixed Models

2.1 Random Effects

The coefficients in Table A3, with standard errors in parentheses, are from linear mixed models with random group intercepts for individuals to account for the error correlation in the repeated measurements (see Galwey, 2007; Gelman and Hill, 2007; Goldstein, 2011; Raudenbush and Bryk, 2002). The random effect model is a partial pooling model, estimating both the overall mean response as well as the deviation in each individual. That is, we assume that an individual in a wave of the panel shares a common mean effect with itself in the other waves. We allow the individual's effect in each wave to deviate from the common effect by a random variable that follows a Guassian distribution. The motivation here is that we avoid estimating an effect by pooling all individuals, which would mask variation in individuals' repeated presence across the waves, and avoid estimating an effect for all individuals separately, which would give poor estimates for low-sample individuals. The p-values are calculated based on Satterthwate's approximations (see Schaalje, McBride and Fellingham, 2002).

Figure A2: Random Effects



The individual random effects from the fully specified model, model 6, in Table A3 are plotted in Figure A2. The zero centered estimates show substantial variability across individuals, which suggests the importance of modeling this error correlation. The quantile quantile plot on the right of the figure displays the sorted values against the expected quantiles. The random effects look normal.

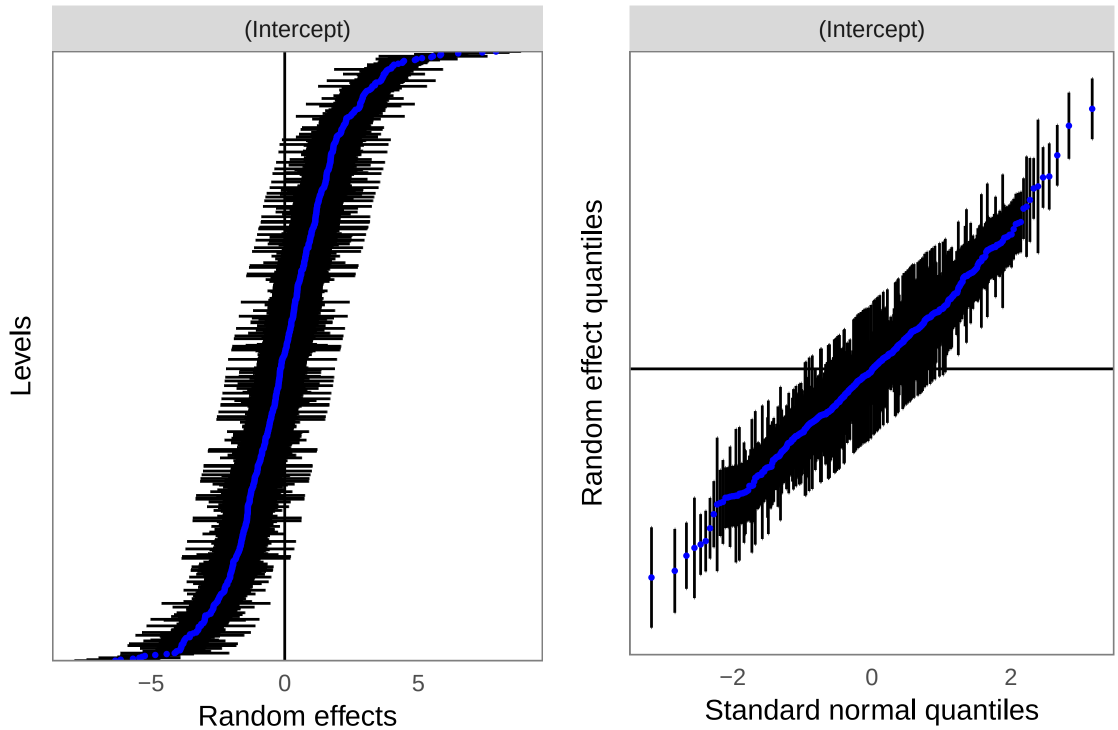
2.2 Awareness of Decisions

Table A2 contains results from a series of models testing our hypotheses in a somewhat different manner than what is presented in the text. In the models in the text we relied on unobserved changes in legitimacy captured by the wave dummies to infer the effects of the decisions. The alternative approach discussed here captures the decision effects via factual questions. Specifically, we use fairly nuanced questions about how the Court ruled in each case to tap awareness of the decision. Respondents had to choose the correct decision rationale—that "The Voting Rights Act is unconstitutional because the list of states required to have their voting laws approved is out of date," and that "The federal Defense of Marriage Act only was unconstitutional"—out of five options of constitutional and unconstitutional decision rationales. Awareness provides an indication of respondents who received the "treatment" of the decision, which is coded as 0 for everyone before the decision, 0 for those after the decision who do not know what the Court decided, and 1 for those who become aware of the decision. This provides us with an alternative and stricter method of capturing the effect of the decision. As we show below, the substantive conclusions are virtually identical to those in the paper. That is, we find strong support with this approach for both the sensitivity to outputs and the negativity bias hypotheses. We also find, again, that the DOMA decision was more salient and had a greater effect.

We believe the approach in the text has a slight advantage, in so far as the tight timing of surveys around each decision allows us to see exactly when legitimacy moves due to the exogenous treatments—and, importantly, how long the effects last. In addition, such an approach provides more conservative effect estimates and may better resemble reality, since many individuals may not have the detailed knowledge to answer the awareness questions correctly but still may have heard of the case decisions and/or some related information. That is, the approach in the text is more akin to an average treatment effect, whereas the awareness approach here is akin to the average treatment effect on the treated. Regardless, we find evidence in support of our hypotheses with both approaches.

As in the body of the paper, we have repeated measures of the same units of observation. Specifically, we have longitudinal data on perceived Court legitimacy, ideological distance and case decision awareness for the same individuals at six points in time. We also have static demographic and political attitude controls. Thus, we follow the same modeling approach as in the paper: the coefficients with standard errors in parentheses in Table A2 are from linear mixed models with random group intercepts for individuals to account for the error correlation in panel responses and fixed effects for the waves. As in the paper, we stepwise introduce the interaction terms—for each decision awareness with party identification, ideology, and policy support—before providing a fully specified model in the last column, model 6. Figure A3 shows the distribution of random effects

Figure A3: Random Effects for Awareness Model



for model 6 and the related quantile-quantile plot, both of which look as expected.

Our primary interest in these models concerns the interactions between the decision awareness variables and the attitudinal variables. These variables test the effect of (understanding) the decisions on legitimacy conditional on party identification strength, ideological distance and issue support. Substantively and statistically significant interaction effects would indicate support for the sensitivity to outputs hypothesis while null findings would suggest support for the alternative stability hypothesis. Differences in the interaction effects among supporters and opponents of the policies, those who are likely happy and unhappy with decisions striking down the laws, may provide support for the negativity bias hypothesis. Before turning to the variables testing our hypotheses, we note that the controls and lower order terms in Table A2 are extremely similar in direction, magnitude and significance to those in the model specification in the text, as expected.

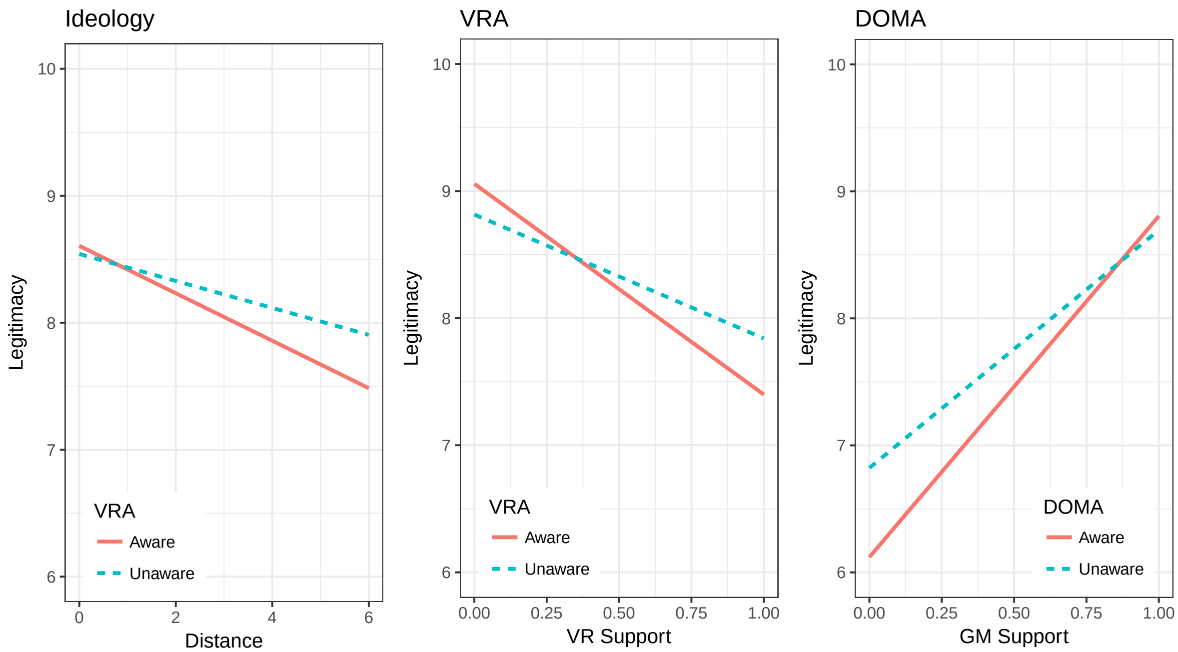
Beginning with the party identification interactions in model 2, we see some evidence of a conditioning effect, where the more strongly identifying with the Republican party leads to a bump in evaluations of the Court given knowledge of the VRA decision. The opposite relationship is found with knowledge of the DOMA case. However, neither of these relationships are substantively meaningful or significant in the fully specified model 6, suggesting that party identification strength has

Table A2: Linear Mixed Model Results

	Supreme Court Legitimacy					
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.013 (0.009)	−0.001 (0.009)	0.0002 (0.009)	−0.002 (0.009)	0.009 (0.009)	0.013 (0.009)
Black	−0.108 (0.374)	−0.680* (0.375)	−0.599 (0.369)	−0.568 (0.381)	−0.282 (0.370)	−0.121 (0.374)
Education	0.064 (0.123)	0.062 (0.128)	0.094 (0.126)	0.087 (0.129)	0.064 (0.125)	0.066 (0.123)
Female	0.261 (0.185)	0.246 (0.194)	0.292 (0.191)	0.272 (0.195)	0.230 (0.189)	0.277 (0.185)
Income	0.200** (0.091)	0.270*** (0.095)	0.246*** (0.094)	0.257*** (0.095)	0.225** (0.093)	0.203** (0.091)
Supreme Court Info	0.206** (0.088)	0.171* (0.091)	0.200** (0.090)	0.174* (0.092)	0.159* (0.090)	0.202** (0.088)
Media Exposure	0.060 (0.070)	0.048 (0.074)	0.042 (0.073)	0.044 (0.074)	0.056 (0.072)	0.058 (0.070)
Political Trust	1.564*** (0.128)	1.524*** (0.132)	1.589*** (0.126)	1.632*** (0.132)	1.535*** (0.126)	1.567*** (0.128)
Political Tolerance	0.092 (0.127)	0.068 (0.133)	−0.003 (0.130)	0.009 (0.132)	0.106 (0.130)	0.088 (0.127)
Gay Family Member	−0.070 (0.184)	−0.036 (0.190)	0.048 (0.187)	0.024 (0.192)	−0.145 (0.187)	−0.078 (0.184)
VRA Awareness	−0.145* (0.085)	−0.379** (0.151)	0.128 (0.136)	0.325* (0.185)	−0.047 (0.193)	0.009 (0.413)
DOMA Awareness	−0.060 (0.096)	0.261 (0.160)	0.128 (0.142)	−0.281 (0.186)	−0.791*** (0.206)	−0.552 (0.435)
Wave 2	−0.154** (0.070)	−0.151** (0.070)	−0.153** (0.070)	−0.150** (0.070)	−0.151** (0.070)	−0.153** (0.069)
Wave 3	0.027 (0.073)	0.047 (0.073)	0.030 (0.072)	0.047 (0.072)	0.047 (0.072)	0.031 (0.072)
Wave 4	−0.079 (0.088)	−0.074 (0.089)	−0.083 (0.088)	−0.075 (0.089)	−0.076 (0.088)	−0.074 (0.088)
Wave 5	−0.002 (0.099)	0.006 (0.099)	−0.015 (0.099)	0.003 (0.099)	0.011 (0.099)	−0.004 (0.099)
Wave 6	−0.097 (0.097)	−0.104 (0.097)	−0.094 (0.097)	−0.099 (0.097)	−0.107 (0.097)	−0.090 (0.097)
Party Id Strength	−0.029 (0.064)	−0.152*** (0.056)				−0.033 (0.065)
VRA Aware * Party Strength		0.074* (0.041)				0.056 (0.055)
DOMA Aware * Party Strength		−0.101** (0.041)				−0.008 (0.055)
Ideological Distance	−0.126*** (0.025)		−0.102*** (0.026)			−0.099*** (0.026)
VRA Aware * Ideol Distance			−0.106** (0.044)			−0.081* (0.046)
DOMA Aware * Ideol Distance			−0.077* (0.044)			−0.046 (0.045)
Voting Rights Support	−1.051** (0.427)			−0.176 (0.410)		−0.969** (0.430)
VRA Aware * VRA Support				−0.874*** (0.305)		−0.684* (0.380)
DOMA Aware * VRA Support				0.432 (0.298)		−0.035 (0.357)
Gay Marriage Support	1.935*** (0.345)				1.702*** (0.299)	1.816*** (0.347)
VRA Aware * GM Support					−0.139 (0.221)	0.316 (0.284)
DOMA Aware * GM Support					0.911*** (0.227)	0.814*** (0.294)
Constant	1.905** (0.892)	3.621*** (0.805)	3.078*** (0.762)	3.035*** (0.786)	1.539* (0.798)	1.923** (0.894)
Random Effect						
# of Groups	650	650	650	650	650	650
Group Standard Deviation	2.146	2.251	2.217	2.264	2.2	2.148
Observations	2,933	2,933	2,933	2,933	2,933	2,933
Log Likelihood	-5,549.420	-5,577.739	-5,565.172	-5,574.622	-5,553.456	-5,541.937
Akaike Inf. Crit.	11,146.840	11,201.480	11,176.340	11,195.250	11,152.910	11,147.870
Bayesian Inf. Crit.	11,290.450	11,339.100	11,313.970	11,332.870	11,290.540	11,339.350

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

Figure A4: Interaction Effects with Decision Awareness



less of a moderating role than ideological distance and issue support. Model 3 finds strong evidence of the conditioning effect of ideological distance in the expected negative directions. Awareness of decisions drop legitimacy conditional on perceiving the Court as more distant to you. However, the effect is limited to the VRA decision in the fully specified model 6. Models 4 and 5 test the capacity of issue support to condition the decision legitimacy relationship. In both cases we find solid evidence of our sensitivity to outputs hypothesis. In Model 4 we see a negative and significant interaction effect for awareness of the VRA decision and support of its underlying issues. In Model 5 we see a positive and statistically significant interactive relationship for awareness of the DOMA decision and support for its underlying issues.

We plot the significant interaction effects from model 6 in Figure A4. The figure illustrates the interaction effects of VRA awareness with both ideological distance and voting rights support, as well as DOMA awareness with gay marriage support. In the left panel we see that as one's ideological distance to the Court increases (i.e., seeing the Court move away from you ideologically) the more negative the VRA decision effect on legitimacy. That is, we find clear evidence of a negativity bias with those who are moving away from the Court ideologically doing so to a larger extent if they are aware of the VRA decision. We find a similar pattern in the issue support interactions in the middle and right panel of Figure A4. Upon receiving information about the Court's position on these issues, people updated their legitimacy assessments in ways consistent with their policy attitudes. In other words, legitimacy was conditional on liking or disliking the Court's outputs. Furthermore, evidence of negativity bias is manifest in both interactions. Consider first the VRA case which was decided in a way contrary to preferences of those who indicated high support on our VRA index. While these VRA supporters generally had lower legitimacy evaluations of the Court, those that learned of this decision dropped their evaluations to a much greater extent. Similarly, for those both aware and unaware of the DOMA decision, greater support for gay marriage leads to higher legitimacy rankings. However, those most supportive of gay marriage reward the Court regardless of their awareness of the decision. In contrast, the "losers," those that are most opposed to gay marriage, were more likely to punish the Court with lower legitimacy evaluations provided they knew that the Court decided against them. In both cases, exposure to the decisions meant a bigger drop among losers and little change among the winners. The fact that the big effects manifest on the figure for voting rights supporters and same sex marriage opponents provides further support for the negativity bias hypothesis.

2.3 Alternative Issue Support Variables

Because the cases and decisions encapsulate a number of associated and complicated issues, in the text we use additive indices to measure policy support for the issues underlying each decision. Below we provide a model that uses only a single survey question most closely related to the case for each case as the issue support variable. The results are largely robust to the issue support variable. We still find support for the sensitivity to outputs and negativity bias hypotheses. In the VRA case, model 4, we again see a significant interaction exactly where we should, with the wave 4 dummy following the decision. The results become a bit muddled, however, in the fully specified model 6, appearing smaller but statistically significant in the earlier waves. Like the results in the text, the VRA support interaction in wave 4 decreases in size, and the effect is noticeably smaller when fighting for explanatory power with ideology, party, and support for gay marriage. In the DOMA case, model 5, the results are also similar to what we present in the text. The interaction is statistically significant following the case decision, wave 5. The effect persists for several weeks to wave 6. Moreover, the results are consistent in size and significance in the fully specified model. These results generally suggest that the issue support findings are fairly robust to the variable coding.

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Table A3: Linear Mixed Model Results

	Supreme Court Legitimacy					
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.011 (0.009)	−0.001 (0.009)	−0.00003 (0.009)	−0.003 (0.009)	0.008 (0.009)	0.010 (0.009)
Black	−0.326 (0.370)	−0.661* (0.375)	−0.599 (0.369)	−0.652* (0.376)	−0.293 (0.370)	−0.336 (0.370)
Education	0.050 (0.123)	0.056 (0.128)	0.091 (0.126)	0.074 (0.128)	0.044 (0.126)	0.056 (0.123)
Female	0.241 (0.186)	0.248 (0.194)	0.286 (0.191)	0.266 (0.194)	0.216 (0.190)	0.245 (0.186)
Income	0.219** (0.092)	0.272*** (0.095)	0.246*** (0.093)	0.268*** (0.095)	0.232** (0.093)	0.223** (0.092)
Supreme Court Info	0.176** (0.088)	0.166* (0.091)	0.193** (0.090)	0.147 (0.092)	0.148* (0.090)	0.169* (0.088)
Media Exposure	0.057 (0.071)	0.045 (0.074)	0.043 (0.072)	0.037 (0.074)	0.058 (0.072)	0.057 (0.071)
Political Trust	1.517*** (0.128)	1.528*** (0.132)	1.589*** (0.126)	1.564*** (0.130)	1.557*** (0.126)	1.521*** (0.128)
Political Tolerance	0.097 (0.129)	0.070 (0.133)	−0.0001 (0.130)	0.062 (0.133)	0.105 (0.130)	0.099 (0.129)
Gay Family Member	−0.101 (0.184)	−0.045 (0.190)	0.040 (0.187)	−0.033 (0.190)	−0.141 (0.187)	−0.114 (0.184)
Wave 2	−0.154** (0.070)	−0.071 (0.142)	−0.054 (0.121)	0.194 (0.252)	−0.078 (0.219)	0.795* (0.447)
Wave 3	0.025 (0.073)	0.131 (0.147)	0.084 (0.124)	0.387 (0.261)	−0.253 (0.226)	0.342 (0.465)
Wave 4	−0.138* (0.082)	−0.301* (0.164)	0.168 (0.144)	0.588** (0.299)	0.080 (0.253)	0.765 (0.510)
Wave 5	−0.105 (0.075)	0.083 (0.153)	0.392*** (0.131)	−0.066 (0.275)	−0.975*** (0.234)	−0.299 (0.481)
Wave 6	−0.187** (0.081)	−0.003 (0.164)	0.079 (0.142)	0.045 (0.293)	−1.098*** (0.246)	−0.440 (0.503)
Party Id Strength	0.009 (0.063)	−0.135** (0.060)				0.025 (0.068)
Wave 2 * Party Strength		−0.026 (0.040)				−0.076 (0.048)
Wave 3 * Party Strength		−0.027 (0.041)				−0.027 (0.050)
Wave 4 * Party Strength		0.052 (0.046)				0.005 (0.055)
Wave 5 * Party Strength		−0.059 (0.043)				0.018 (0.052)
Wave 6 * Party Strength		−0.061 (0.046)				0.014 (0.055)
Ideological Distance	−0.132*** (0.025)		−0.058 (0.036)			−0.056 (0.036)
Wave 2 * Ideol Distance			−0.042 (0.043)			−0.043 (0.043)
Wave 3 * Ideol Distance			−0.022 (0.044)			−0.020 (0.044)
Wave 4 * Ideol Distance			−0.129*** (0.049)			−0.122** (0.049)
Wave 5 * Ideol Distance			−0.213*** (0.046)			−0.202*** (0.046)
Wave 6 * Ideol Distance			−0.112** (0.049)			−0.103** (0.049)
Voting Rights Support	0.091 (0.116)			0.344*** (0.122)		0.210* (0.126)
Wave 2 * VRA Support				−0.116 (0.082)		−0.158* (0.089)
Wave 3 * VRA Support				−0.115 (0.085)		−0.194** (0.092)
Wave 4 * VRA Support				−0.245** (0.097)		−0.208* (0.106)
Wave 5 * VRA Support				−0.012 (0.089)		−0.095 (0.097)
Wave 6 * VRA Support				−0.081 (0.095)		−0.208** (0.103)
Gay Marriage Support	0.491*** (0.102)				0.439*** (0.096)	0.409*** (0.110)
Wave 2 * GM Support					−0.023 (0.065)	−0.046 (0.076)
Wave 3 * GM Support					0.093 (0.067)	0.123 (0.079)
Wave 4 * GM Support					−0.070 (0.075)	−0.004 (0.089)
Wave 5 * GM Support					0.272*** (0.069)	0.276*** (0.082)
Wave 6 * GM Support					0.285*** (0.073)	0.336*** (0.086)
Constant	1.293 (0.943)	3.614*** (0.807)	3.030*** (0.763)	2.178*** (0.831)	1.565* (0.821)	0.977 (0.974)
Random Effect						
# of Groups	650	650	650	650	650	650
Group Standard Deviation	2.158	2.25	2.215	2.256	2.204	2.159
Observations	2,936	2,936	2,936	2,936	2,936	2,936
Log Likelihood	-5,559.004	-5,587.567	-5,568.737	-5,583.845	-5,555.818	-5,561.486
Akaike Inf. Crit.	11,162.010	11,223.140	11,185.480	11,215.690	11,159.640	11,206.970
Bayesian Inf. Crit.	11,293.670	11,366.770	11,329.110	11,359.330	11,303.270	11,458.330

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

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