Supplementary Appendix to "How do Public Officials Learn About Policy? A Field Experiment on Policy Diffusion"

Miguel M. Pereira
University of Southern California
m.pereira@usc.edu

This supplementary appendix includes the following sections:

- **Appendix A - Email Sent to Local Officials**
  This section presents an example of the full text of the email sent by Welcoming America to local officials as part of the dissemination campaign, and the links provided in the email.

- **Appendix B - Sample**
  In this section I describe the data sources used to create the sample of local officials, and the open rates.

- **Appendix C - Measuring Officials' Partisanship**
  This section describes how I created the measure of individual partisanship.

- **Appendix D - Descriptives and Main Results**
  This section includes descriptive statistics of the sample of local officials in the study, the outcome variables, and a series of covariate balance tests. Additionally, it includes the regression tables used to produce the results reported in the main text.

- **Appendix E - Sensitivity Analyses**
  A series of additional tests to assess the robustness of the main analysis.

- **Appendix F - Results by District Competitiveness**
  This section explores how the political composition of the district moderates the effects of partisan cues on policy learning.

- **Appendix References**

Appendix A - Email Sent to Local Officials

All emails were sent from the project manager of Certified Welcoming and included the following subject: "**Introducing a New Certification Program for Local Governments**". Figure A1 presents an example of the main body of text in the email sent to public officials. Figure A2, in turn, is a screenshot of the links displayed in the footer of all emails. The emails were sent through GetResponse, an email marketing service that allows users to track which subjects opened the email and clicked on the various links provided in the message.

Figure A1: Example of email sent with Democratic endorsement.

Dear [[title]] [[name]],

As communities compete to attract business and diverse talent, a new program is helping my hometown of Dayton, Ohio build a competitive advantage. **Certified Welcoming** is an innovative approach to attract and retain talent, create workforce opportunities, and advance a community that everyone can call home.

The **Certified Welcoming** designation sets cities and counties apart from their competitors by demonstrating their commitment to a diverse and talented workforce – something that Fortune 500 companies, like Amazon and others, look for when they open up new locations. We know that Certified Welcoming places are places where everyone – newcomers and long-term residents – benefits from the economic advantage and cultural richness.

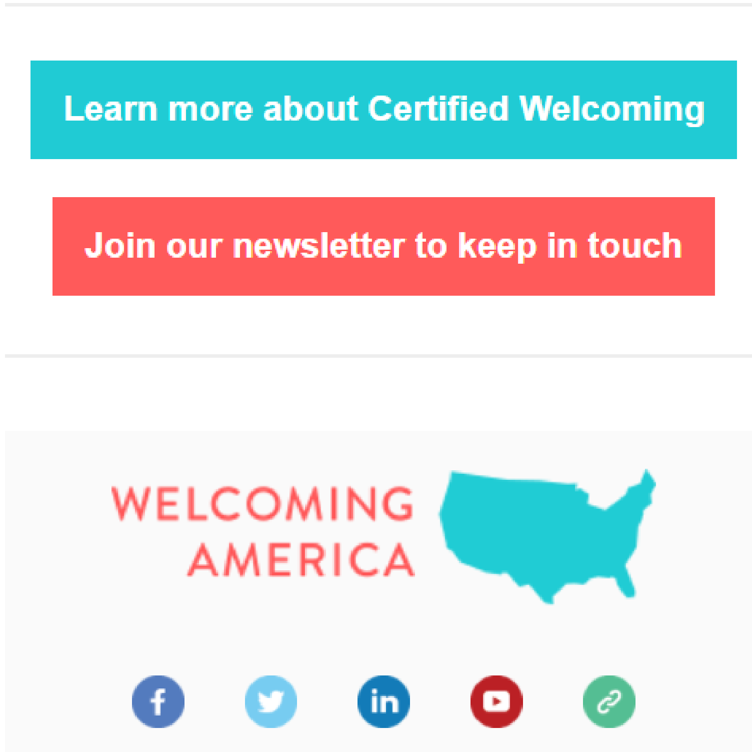
Republicans in Salt Lake County recently joined Certified Welcoming. The program is part of an effort to attract, retain, and engage immigrants in the city.
"Immigrants are families, homeowners, entrepreneurs, taxpayers and neighbors. Welcoming them and their contributions benefits our community," said Republican Lane Beattie from Salt Lake County.

Certified Welcoming is a program of Welcoming America, a national nonpartisan nonprofit. **Welcoming America** is leading a movement of communities to build more cohesive, prosperous places where everyone – including immigrants and refugees – can belong and thrive. We work to create positive change, more stable democratic foundations, and vibrant economies for everyone.

If you are curious about the program and want to learn more, visit us at CertifiedWelcoming.org and **sign up for our e-mail campaign** on the Welcoming Standard. Please also feel free to contact me directly at certified@welcomingamerica.org.

[redacted]
Certified Welcoming Manager

Figure A2: Links in email footer.



Appendix B - Sample

The emails of local elected officials were collected from two main sources: the Google Civic Information API, and the American Municipal Officials Survey (AMOS 2017). The Civic Information API offers information about political geographic divisions and elected representatives from the federal to the local level, including their updated contact information. According to the website, coverage for county elected officials was approaching 100% at the time of the study. All valid emails from city and county officials were scrapped in January 2018. More details about this open-access service available at `https://developers.google.com/civic-information/`. The AMOS sample, in turn, only includes municipal legislators. I merged the two datasets and thoroughly checked for inconsistencies. When a given public office had more than one email associated, I visited the respective website to ensure that the contact information was up to date.

Table B1 provides the number of emails delivered and opened by treatment condition. The original sample includes 20,893 emails but about 9% of the addresses (2,152) were no longer valid when the study was fielded. Using email delivery as the baseline (18,741), the overall open rate was 35.8% (6,713). There are no meaningful differences in compliance across conditions.[1] The analyses conducted below are based on politicians who opened the email, since only these were exposed to the treatment. As described in Appendix A, the email subject, salutation, and the first two full paragraphs of the main body of text, were the same across treatment groups. Hence, it is very unlikely that subjects were exposed to the treatment before opening the email, which could introduce post-treatment bias (Coppock 2019). Still, the same substantive results are obtained when the full sample of contacted officials is included in the analysis (cf. Figure E6). Restricting the sample to those who were exposed to the campaign message allows me to directly estimate the treatment effects. Table D1 (Appendix D) describes the distribution of local officials by state. Although there is some variation due to data availability, the data suggests a wide coverage of local governments from all 50 states.

The subjects treated in the study are the officials' email addresses and not the representatives themselves. This practice is common in audit studies (e.g., Butler and Broockman 2011; Nyhan and Reifler 2015) and requires assuming that staffers who open the email acted on behalf of the respective elected official. In the context of this study, this assumption is unlikely to have meaningful consequences since for the vast majority of local offices there are no resources available to support staffers.

Table B2 compares the characteristics of subjects who opened the email and took part in the study, and those who chose not to open the email. For the descriptive variables available, the differences across groups are substantively small. As an example, the average county-level Democratic vote share in the 2012 presidential election was 47.2% among subjects who did not open the email, and 48.0% among subjects who took part in the study. The difference (0.8 percentage points) is statistically significant due to the large sample sizes, but residual. The exception to this pattern is the data source. Local officials whose contact information came from AMOS were 13 percentage points less likely to open the email than subjects whose information came from the Google Civic Information API. This difference was expected since at the time of the study the AMOS dataset was already two years old, and therefore was more likely to include contacts of officials who no longer were in office. Finally, logged population size also predicts the likelihood that a local official opened the email (p-value < 0.01). However, the difference is again substantively small (0.16).

[1] The p-value for a difference in means from a one-way ANOVA is 0.18.

Table B1: Number of emails delivered and opened, by endorsement condition.

		Type of Endorsement		
	Total	Bipartisan	Democratic	Republican
Emails Delivered	18,741	6,270	6,274	6,197
Emails Opened	6,713	2,186	2,263	2,264
% Opened	35.8	34.9	36.0	36.5

Table B2: Differences between subjects who opened the email and subjects who did not open the email.

	Did not open email	Opened email	p-value
Democratic vote share	0.47	0.48	<0.01
Population (log)	11.67	11.83	<0.01
AMOS (data source)	0.63	0.56	<0.01
Number of elected officials	8.10	8.26	0.11
Republican†	0.17	0.19	<0.01
Democrat†	0.13	0.14	0.10
N	14,679	6,214	-

Note: Entries are means of descriptives of subjects who opened the email and participated in the study, and subjects who did not open the email, along with p-values for the differences in means.†Republican/Democrat identifies officials for which individual partisanship was available.

Appendix C - Measuring Partisanship

Ideally, to measure officials' partisanship I would rely on party labels from local elections. Unfortunately, over 80% of local elections in the US are non-partisan (Trounstine 2010; Tausanovich and Warshaw 2014). For larger communities, information on the partisanship of representatives in non-partisan seats is often available and has been used in recent scholarship (de Bennedictis-Kressner and Warshaw 2016). However, for smaller towns and counties that represent the majority of local governments this information is not available.[2] With this constraint in mind, I collected individual partisanship data for 32% of the sample. The data come from the Google Civic Information API. For the remaining cases, I relied on county-level presidential vote shares to infer the partisanship of elected officials. Representatives from counties that voted Democrat/Republican in 2012 are coded as Democrat/Republican.[3] This approach induces measurement error. However, recent scholarship suggests that the magnitude of this error should be limited. The correlation between vote shares in presidential elections and the partisanship of county legislators and mayors ranges from 0.7 to 0.8 in 2014, and this relationship has increased over time (Warshaw 2019). Local communities in the US – particularly smaller ones for which data on individual partisanship is less likely to be available – tend to be politically homogeneous (Enos 2017).

To assess the robustness of this empirical strategy, I compared the two measures of partisanship among the subsample of officials with data on individual-level partisanship (32% of the full sample). The bivariate correlation is 0.81. Additionally, the results are robust to the exclusion of officials from more competitive districts, where this empirical strategy may induce more noise (cf. Figure E1).

Appendix D - Descriptives and Main Results

Table D1 describes the share and number of local officials in the study, by state. Figure D1, in turn, displays a histogram of the variable *Degree of Engagement*: the number of links clicked by local officials. The variable ranges from 0 to 6, with a mean value of 0.8. Table D2 provides different balance tests. The upper panel describes t-tests of differences in means for a series of relevant confounders, by treatment group. The lower panel, in turn, presents likelihood ratio tests comparing model fit of logit models explaining treatment assignment as a function of all six confounders, relative to a null model. The analyses reveal

[2] As described in the main text, randomization was blocked by community size to account for this and other meaningful differences across communities.

[3] The same patterns are obtained with the election results from 2016, or when counties that switched majority between 2012 and 2016 are excluded, as described in Appendix E.

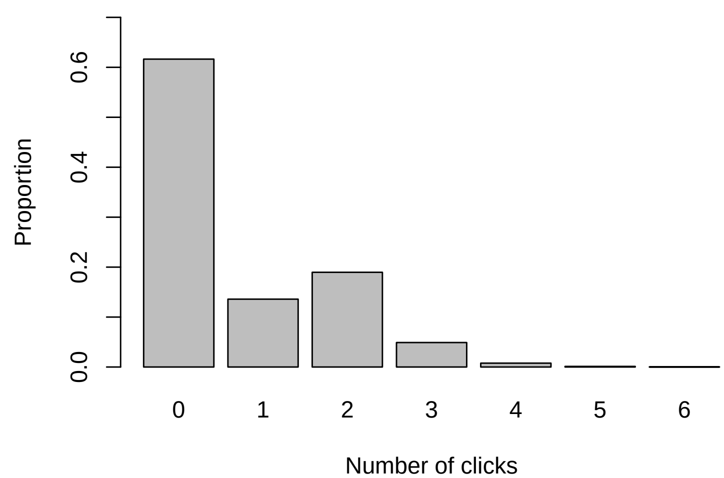
balanced conditions. Table D3 displays the regression tables used to produce the coefficient plots presented in Figure 1. Finally, Tables D4 and D5 provide t-tests for the differences in means across all combinations of treatments and outcomes.

Table D1: Study participants by state.

State	N	%	State	N	%	State	N	%	State	N	%
AK	22	0.30	IL	385	5.70	NC	185	2.80	SC	120	1.80
AL	74	1.10	IN	67	1.00	ND	9	0.10	SD	29	0.40
AR	26	0.40	KS	87	1.30	NE	28	0.40	TN	75	1.10
AZ	185	2.80	KY	55	0.80	NH	20	0.30	TX	176	2.60
CA	212	3.20	LA	72	1.10	NJ	143	2.10	UT	66	1.00
CO	86	1.30	MA	60	0.90	NM	32	0.50	VA	200	3.00
CT	33	0.50	MD	66	1.00	NV	34	0.50	VT	2	0.00
DC	5	0.10	ME	38	0.60	NY	418	6.20	WA	116	1.70
DE	21	0.30	MI	381	5.70	OH	201	3.00	WI	181	2.70
FL	146	2.20	MN	125	1.90	OK	46	0.70	WV	12	0.20
GA	165	2.50	MO	75	1.10	OR	405	6.00	WY	31	0.50
IA	661	9.80	MS	25	0.40	PA	1019	15.20	-		
ID	26	0.40	MT	44	0.70	RI	23	0.30	-		

Note: Entries are the number and share of local officials in the study, by state.

Figure D1: Distribution of variable *Degree of Engagement*.



Note: Bars describe the proportion of respondents by the number of different links clicked.

Table D2: Covariate balance across treatment groups.

	Own party	Other party	Bipartisan	p-value
Democratic vote share	0.48	0.48	0.48	0.27
Population (log)	13.07	12.97	12.97	0.72
AMOS (data source)	0.56	0.57	0.57	0.78
# of elected officials	8.21	8.36	8.16	0.66
Republican†	0.20	0.19	0.20	0.96
Democrat†	0.15	0.14	0.12	0.11
N	2,270	2,257	1,046	-
Likelihood Ratio Test:				
Own party - Other party	$\chi^2(7) = 5.1$		$Pr(> \chi^2) = 0.53$	
Own party - Bipartisan	$\chi^2(7) = 11.7$		$Pr(> \chi^2) = 0.07$	
Bipartisan - Other party	$\chi^2(7) = 9.9$		$Pr(> \chi^2) = 0.13$	

Note: Entries in the top panel are means of covariates across treatment conditions and p-values correspond to F tests of difference in means. The model fit of logistic regressions with treatment assignments as a function of all covariates was compared with the respective null model. The likelihood ratio tests described in the bottom panels do not reject the null models.†Republican/Democrat identifies officials for which individual partisanship was available.

Table D3: The effects of partisanship on policy learning, complement to Figure 1.

	Policy Interest	Policy Engagement
Other party	−0.041	−0.085
	(0.014)	(0.030)
Bipartisan	−0.035	−0.122
	(0.018)	(0.038)
Constant	0.406	0.770
	(0.010)	(0.021)
Observations	5,573	5,573
R^2	0.002	0.002

Note: Entries are OLS coefficients of the treatment effects of partisan endorsements on policy interest (clustered standard errors in parenthesis). Specific outcome variables in column headers. Same party endorsement as baseline category.

Table D4: T-tests for differences in policy interest across all combinations of treatments.

Endorsement	(1)	(2)	(3)
Same party	.406	.406	-
Other party	.365	-	.365
Bipartisan	-	.371	.371
Difference	.041	.035	$-.006$
T-statistic	2.84	1.92	$-.35$
P-value	$<.01$	.06	.73
N	4,527	3,369	3,250

Note: Entries are means of policy interest by type of endorsement. T-statistics and p-values from two-sample t-tests.

Table D5: T-tests for differences in policy engagement across all combinations of treatments.

Endorsement	(1)	(2)	(3)
Same party	.770	.770	-
Other party	.685	-	.685
Bipartisan	-	.648	.648
Difference	.085	.122	0.037
T-statistic	2.78	3.31	1.01
P-value	$<.01$	$<.01$	.31
N	4,527	3,369	3,250

Note: Entries are means of policy engagement by type of endorsement. T-statistics and p-values from two-sample t-tests.

Appendix E - Sensitivity Analyses

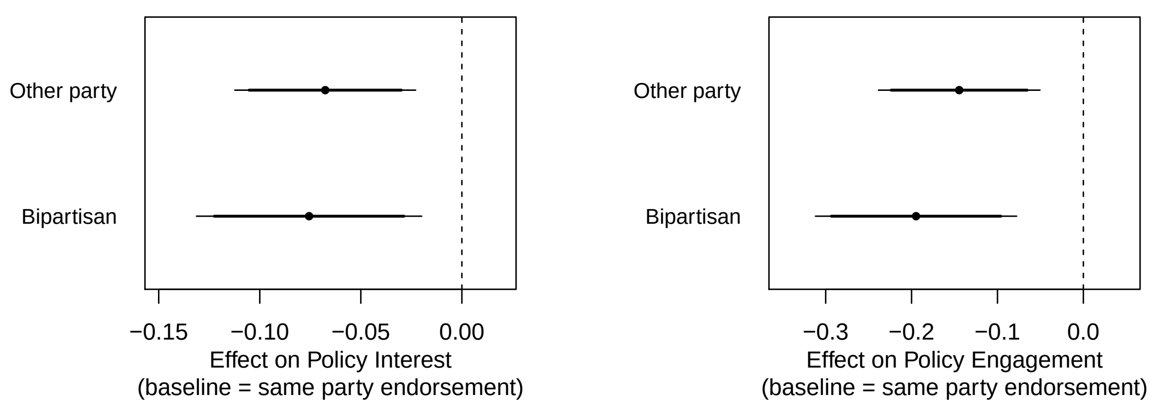
In this section, I briefly describe a series of sensitivity analyses to assess the robustness of the main findings. Figure E1 replicates the main findings excluding officials in politically competitive districts. Competitive communities are defined as those where the absolute presidential vote margin is below the median value (10.0 points). These are regions where the measure of partisanship adopted may be more prone to measurement error. The results are robust to the exclusion of representatives from competitive districts. Table E1 estimates treatment effects for different measures of policy interest: (1) whether an official visited the policy website; (2) join the newsletter of the organization; or (3) visited the social media accounts of Welcoming America. The results are substantively the same when each link is analyzed separately.

Figure E2 describes the effects of different partisan endorsements among Democrats (panels a and b), and Republicans (panels c and d). The differences between out-partisan and bipartisan endorsements are indistinguishable from zero in both instances. However, co-partisan endorsements only generate significantly more interest than out-partisan and bipartisan endorsements among Democrats. The effects for Republicans are generally in the same direction but smaller and indistinguishable from zero. I am cautious in the interpretation of treatment heterogeneity in this context. These relationships are not causally identified and partisanship correlates with important confounders that are likely associated with interest in the policy under consideration: community size, geographical proximity to the endorser, or the size of the immigrant community living in the constituency. That said, one possible explanation for this pattern is that partisan cues only play a role above a certain threshold of policy interest. This is consistent with prior research showing that the ideological tenor of a policy moderates the willingness of public officials to learn from each other (Butler et al. 2017). Alternatively, Democrat and Republican officials may vary systematically in the way they respond to partisan endorsements, regardless of the issue under consideration. However, this explanation is not consistent with existing survey evidence showing that partisan bias in policy learning operates similarly for conservative policies (Butler and Pereira 2018). The same substantive results are obtained when partisanship is measured based exclusively on county-level results from the 2016 presidential election. Co-partisan bias in policy learning, in the context of this study, is mainly driven by officials in constituencies with Democratic majorities.

Figure E3, in turn, replicates the main analyses with both versions of the bipartisan endorsement. To avoid order effects, the bipartisan treatment randomized the order in which parties were presented in the vignette. However, due to a coding error, one of the links in the email was broken for one of these versions. Hence, to ensure comparability across conditions, this random subgroup was dropped from the main analyses. Figure E3 shows that similar results are obtained when both versions of the bipartisan endorsement are included.

The main findings are also robust to different measures of partisanship. Figures E4 and E5 describe treatment effects when partisanship is measured based on 2016 presidential results and when only counties that voted on the same party in 2012 and 2016 are included in the analyses (87% of the sample). Figure E6, in turn, provides the intent-to-treat estimates of the different partisan endorsements on policy interest. The outcome variables for subjects who did not open the email are coded as 0. Without opening the email, it was not possible for subjects to click in any of the links provided in the body of the message. The same substantive results are obtained when local officials who did not open the email are also included in the analysis.

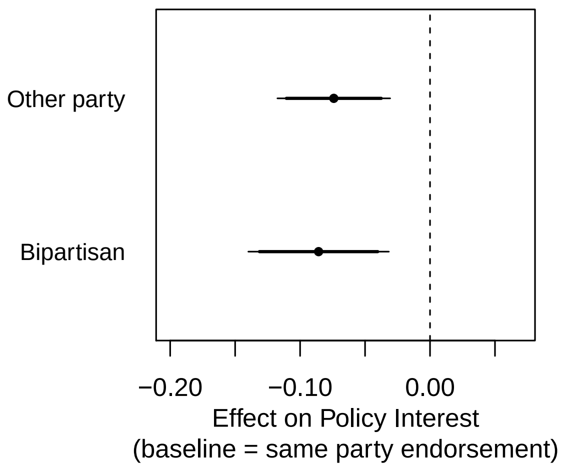
Figure E1: The effects of partisan endorsements on policy interest, excluding officials in competitive districts.



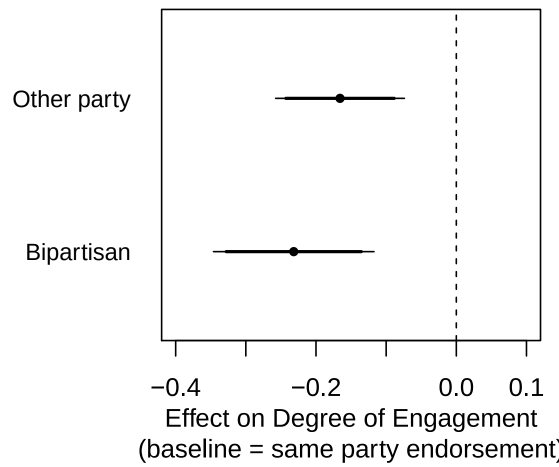
(a) Policy Interest (b) Degree of Engagement

Note: Replication of main analyses excluding local officials from competitive districts. Points are estimates of the treatment effects of partisan endorsements on (a) *Policy Interest* and (b) *Degree of Engagement*. Thin/Thick horizontal bars represent 95%/90% confidence intervals from linear models regressing the measures of policy interest on the different treatments.

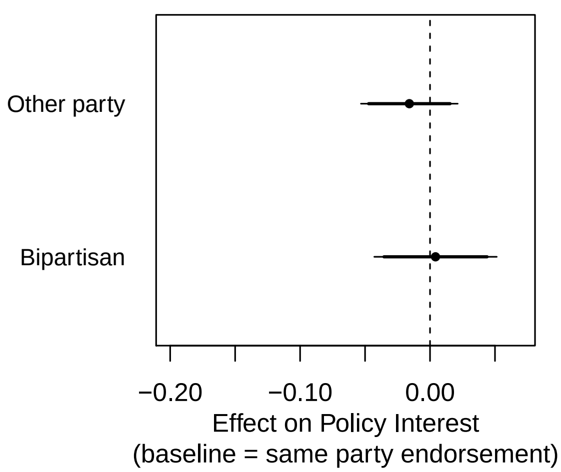
Figure E2: The effects of partisan endorsements on policy interest, by officials' partisanship.



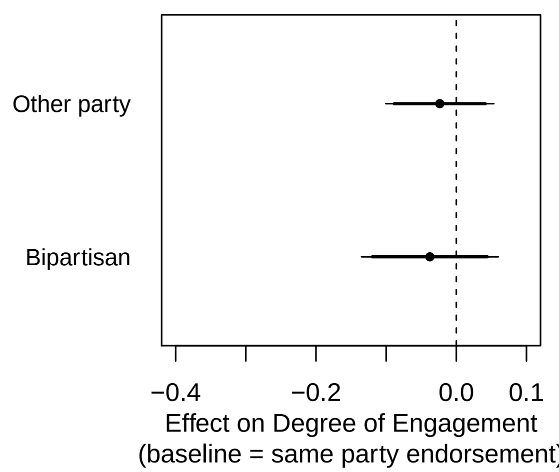
(a) Policy Interest
Democratic officials



(b) Degree of Engagement
Democratic officials



(c) Policy Interest
Republican officials



(d) Degree of Engagement
Republican officials

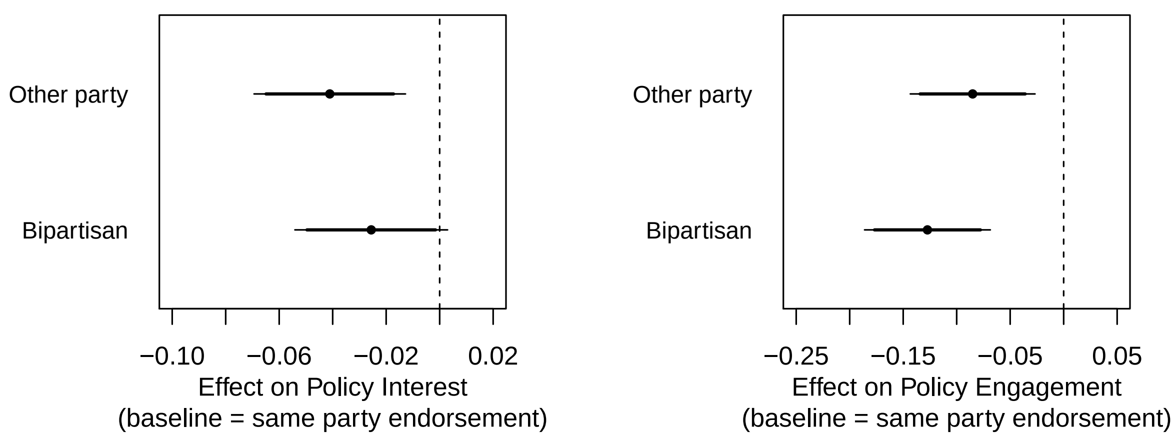
Note: Points are estimates of the treatment effects of partisan endorsements on (a/c) *Policy Interest* and (b/c) *Degree of engagement*. Thin/Thick horizontal bars represent 95%/90% confidence intervals from linear models regressing the measures of policy interest on the different treatments. Panels a/b report results among Democrats, while panels c/d report results among Republicans.

Table E1: The effects of partisan endorsements for different measures of policy interest.

Endorsement dyads	Visit Website	Join Newsletter	Social Media Clicks
Co-Partisan v. Out-Partisan	2.9	1.9	0.04
	(0.01)	(0.13)	(0.05)
Co-Partisan v. Bipartisan	3.1	5.2	0.04
	(0.03)	(0.00)	(0.09)
Bipartisan v. Out-Partisan	0.2	−3.3	0.00
	(0.88)	(0.03)	(0.92)

Note: Entries are differences in percentages (columns 1-2) and average differences in the number of links clicked (column 3) for each endorsement dyad described in the rows (e.g, *Co-Partisan v. Out-Partisan* is the difference between co-partisan and out-partisan endorsements). *P*-values from a two sample t-test in parenthesis. Columns represent different measures of policy interest based on click tracking.

Figure E3: Replication of main results with both versions of bipartisan endorsement.

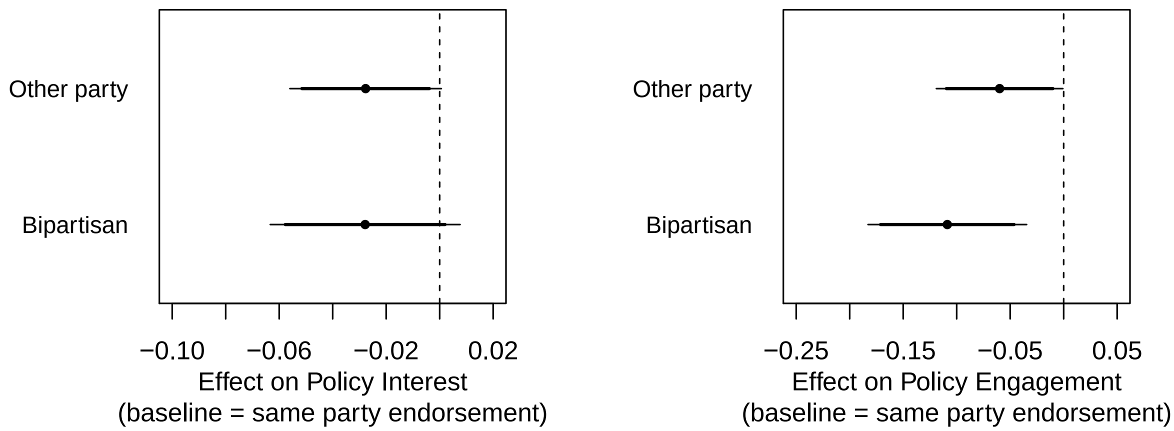


(a) Policy Interest

(b) Degree of Engagement

Note: Replication of main analyses with both versions of bipartisan treatment. Points are estimates of the treatment effects of partisan endorsements on (a) *Policy Interest* and (b) *Degree of Engagement*. Thin/Thick horizontal bars represent 95%/90% confidence intervals from linear models regressing the measures of policy interest on the different treatments.

Figure E4: Partisan effects on policy interest with alternative measure of partisanship.

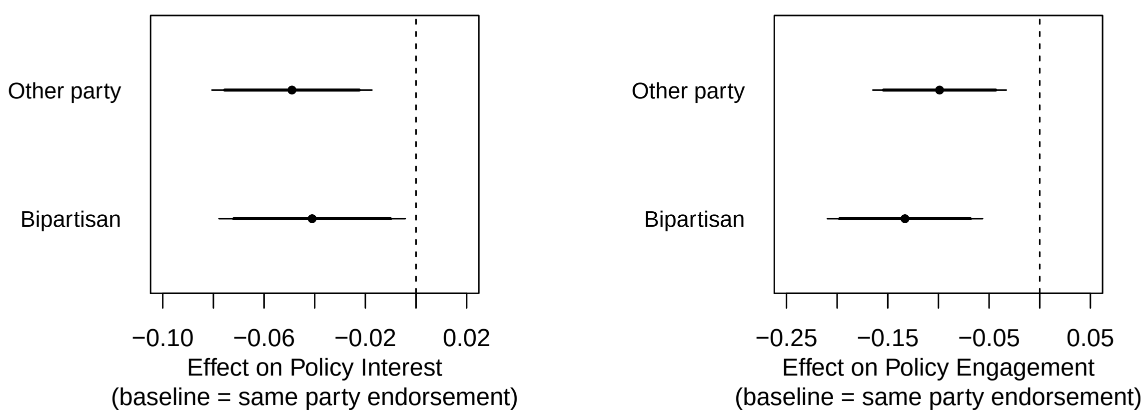


(a) Policy Interest

(b) Degree of Engagement

Note: Replication of main analyses based on 2016 county-level presidential results. Points are estimates of the treatment effects of partisan endorsements on (a) *Policy Interest* and (b) *Degree of Engagement*. Thin/Thick horizontal bars represent 95%/90% confidence intervals from linear models regressing the measures of policy interest on the different treatments.

Figure E5: Partisan effects on policy interest among same-party county majority in 2012 and 2016.

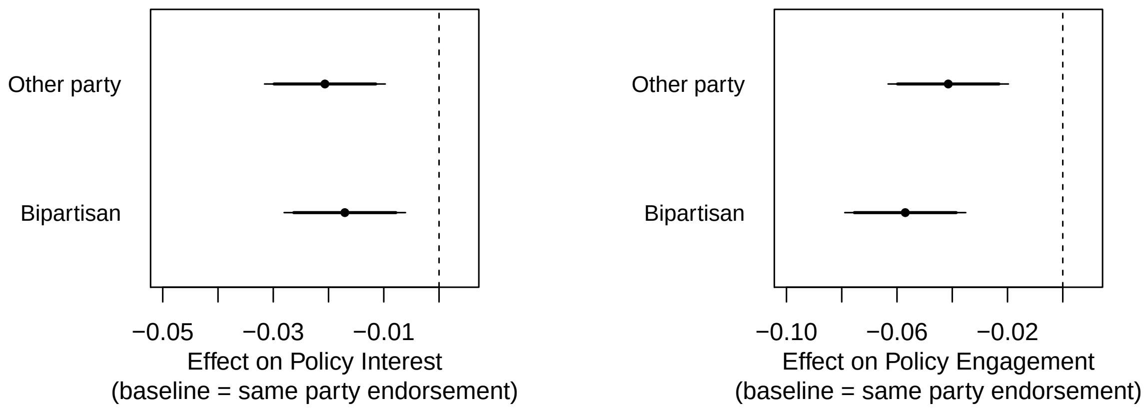


(a) Policy Interest

(b) Degree of Engagement

Note: Replication of main analyses excluding officials from counties that switched majority party between 2012 and 2016. Points are estimates of the treatment effects of partisan endorsements on (a) *Policy Interest* and (b) *Degree of Engagement*. Thin/Thick horizontal bars represent 95%/90% confidence intervals from linear models regressing the measures of policy interest on the different treatments.

Figure E6: Intention-to-treat (ITT) effects of partisan endorsements on policy interest.



(a) Policy Interest

(b) Degree of Engagement

Note: Replication of main analyses including all local officials who were originally contact, including those who did not open the email. Points are estimates of the ITT effects of partisan endorsements on (a) *Policy Interest* and (b) *Degree of Engagement*. Thin/Thick horizontal bars represent 95%/90% confidence intervals from linear models regressing the measures of policy interest on the different treatments.

Appendix F - Results by District Competitiveness

In this section, I explore how the composition of the electorate may moderate partisan-based learning. The goal of this exploratory analysis is to shed an initial light on why public official may rely on partisan cues when learning about new policies. The results in the main text suggest that bipartisan endorsements generate no more interest than out-partisan endorsements. This pattern may be driven by representatives from communities that are either mainly Republican or mainly Democratic (Bishop 2009). Americans tend to live in politically homogeneous communities (Enos 2017). Local officials in these contexts may have little incentives to consider positions of compromise.

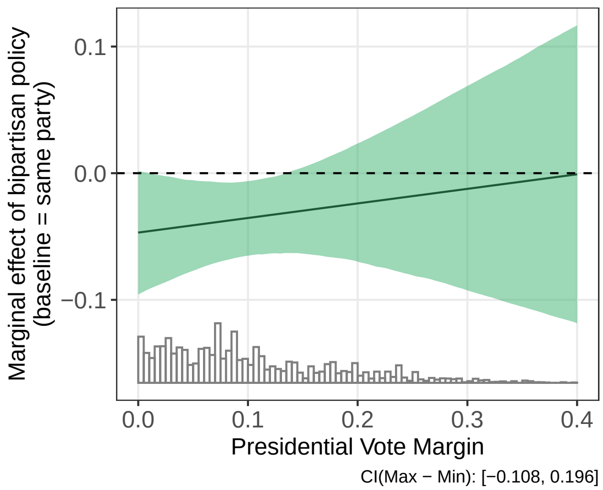
In more competitive districts, in turn, positions of compromise may attract more interest. Legislators tend to converge ideologically in communities with a more balanced share of Republican and Democratic voters (Ansolabehere et al. 2001; Burden 2004; Carson and Williamson 2018). Representatives in more competitive districts also tend to vote more moderately than their peers in more lopsided districts (Erikson and Wright 2000). Hence, if partisanship is used as an ideological cue, bipartisan policies may become increasingly attractive in more competitive contexts (relative to both co-partisan and out-partisan policies).[4]

To test these expectations, I created a measure of competitiveness based on the county-level absolute margin of victory in the previous presidential election. Smaller values suggest higher levels of competitiveness. This measure was then interacted with the treatment conditions to assess how district composition moderates the effects of partisan cues. The bipartisan endorsement was omitted to serve as baseline.

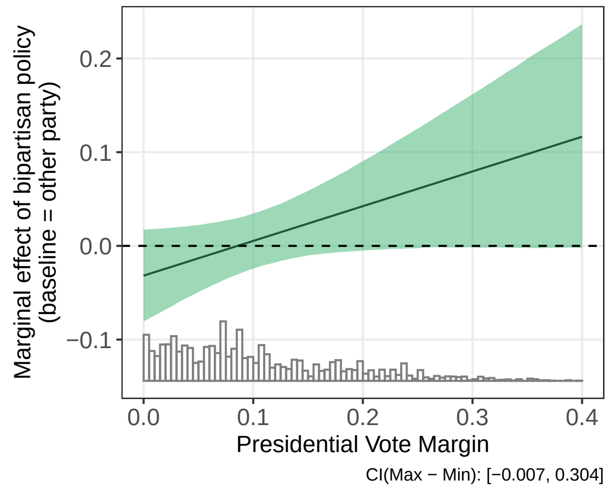
Figure F1 summarizes the results from two linear models, with *Policy Interest* (panels a and b) and *Degree of Engagement* (panels c and d) as the outcomes. There is no evidence that legislators in more competitive districts are revealing more interest in policies endorsed by both parties. Panels a and c present the differences in policy interest between bipartisan and co-partisan endorsements. For most of the support range of competitiveness, co-partisan endorsements are favored over bipartisan endorsements. In turn, panels b and d reveal no meaningful distinctions between out-partisan and bipartisan endorsements regardless of the levels of competitiveness in the district. This is true for both outcome variables. Based on the arguments articulated above, if politicians were simply inferring ideological proximity from partisan cues, those from more competitive districts should be more likely to favor bipartisan policies over out-partisan policies. The evidence does not support this argument.

[4] An alternative form of ideological-based learning consistent with the results obtained in the main analysis is that officials decide which policies to seek information about based on some cutpoint along the ideological continuum. If this cutpoint is somewhere between the co-partisan and the bipartisan signals, we should not expect a meaningful difference in interest between bipartisan and out-partisan endorsements. However, for reelection-seeking officials this cutpoint is likely associated with constituency preferences. Therefore, district composition should still moderate the effect of different partisan signals. The evidence provided in this section is also not consistent with this form of ideological-based learning.

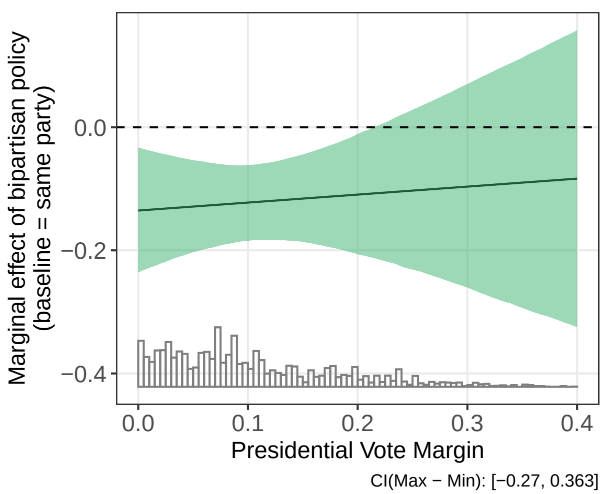
Figure F1: The effects of bipartisan policy endorsements on *Policy Interest* (panels a and b) and *Degree of Engagement* (panels c and d) by levels of political competitiveness.



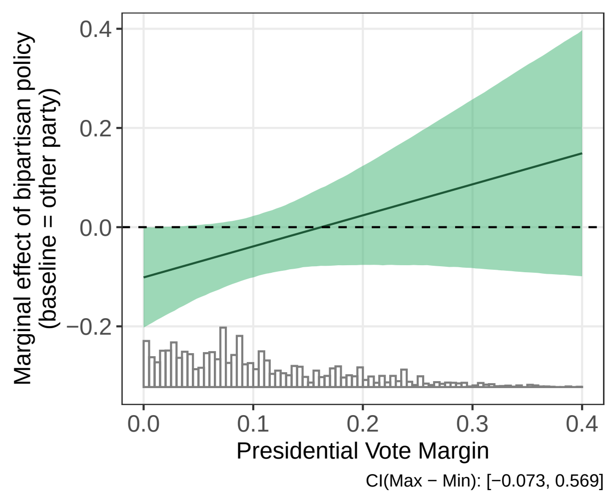
(a) Bipartisan v. Same party



(b) Bipartisan v. Other party



(c) Bipartisan v. Same party



(d) Bipartisan v. Other party

Note: The y-axis represents estimated differences in *Policy Interest* and *Degree of Engagement* between officials who received a bipartisan endorsement and officials who received an endorsement from their own party (Panels a and c)/other party (Panels b and d). The x-axis displays a measure of electoral competitiveness based on the absolute margin of victory in the last presidential election. The shaded bars indicate 90% confidence intervals, and the distribution of *Presidential Vote Margin* is plotted at the bottom.

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