

APPENDIX:
Local news and the electoral incentive to invest in infrastructure

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A. Case selection

Drinking water has several features making it a favorable case for testing pandering behavior in a local political setting. Government participation in drinking water provision resides almost exclusively at the local level, differentiating it from transportation and other forms of infrastructure that are a shared responsibility across levels of government. Most cities and towns with at least 3,300 people own and operate their own water systems, and many counties do as well. Even though some local government officials do not directly oversee a water system, they largely recognize water as a critical local function. (Our results are robust to omitting 26 respondents who indicated in open-ended survey responses that their jurisdictions do not provide water service.) Water systems rely on revenue generated locally through user fees, which are visible and directly connected to water service. In contrast, the benefits of water system investments are much less visible. Projects to maintain and upgrade deteriorating infrastructure almost never produce improvements in water quality that are detectable to a water consumer, and politicians have little opportunity to claim credit for preventing disruptions from natural hazards. Underground pipes make it impossible for the public to observe their deterioration and widespread leakage. Finally, drinking water service is relatively uncontroversial as compared to other local services, prompting little disagreement over its necessity or the form of its delivery.

The text of the vignette outlines a bond-financed infrastructure maintenance project recommended by a consultant that would require rates to rise by one-third for the average household. Although this is a large rate increase, it is not uncommon for a major drinking water project. In open-ended responses, several officials indicated that their local governments had faced a similar decision, including one who reported, “We recently had to raise our water rates 400% to keep the water flowing.” A study of 178 municipally-owned water systems showed that over half had raised their rates by more than 15% in a year at least once within a period of ten years (Hansen, Eskaf, and Mullin 2021).

B. Survey information

	Sample: City	Population: City	Sample: County	Population: County
City or county:				
Population, mean	27,439	15,046	98,964	96,787
% college graduate, mean	30%	26%	22%	21%
% urban, mean	71%	57%	46%	41%
County GOP vote share, mean	52%	56%	60%	64%
	Sample: City	Complete case: City	Sample: County	Complete case: County
Elected official:				
Female	33%	33%	20%	17%
White, non-Hispanic	87%	87%	85%	88%
College graduate	65%	67%	61%	67%
Democrat or lean Democrat	40%	41%	27%	24%
Republican or lean Republican	49%	48%	67%	71%
Competition in last election	61%	61%	69%	69%
Ambitious	89%	89%	91%	91%
N	388	317	75	58

Table A1. Sample characteristics. The upper section's full sample and population characteristics for geographic units were provided by CivicPulse. The sample mean for city population size is inflated by one observation from a very large city; omitting that observation, the sample mean is 23,564. The lower section's full sample individual data include respondents who viewed the survey's second module and are used in Model (3) in Table A8 (Appendix J). The lower section's complete case subsample viewed the water module only and are used in Model (5) in Table A4 (Appendix G). N for White, non-Hispanic (city) = 309.

The experiment was part of a national online survey of local government officials conducted by CivicPulse from April 2 to May 14, 2020. CivicPulse is a nonprofit organization that maintains comprehensive lists of U.S. government officials and their publicly available contact information for the purpose of conducting surveys on government issues. For this survey, they invited a random sample of township, municipal, and county elected officials to participate.

The recruitment email and survey questionnaire were approved by the Duke University Campus Institutional Review Board (Protocol 2020-0439). Participation in the survey was completely voluntary and participants were not offered any compensation. By standard practice and in conformance with all state laws, CivicPulse does not compensate government officials for participation in its surveys. The recruitment email informed participants that the survey would generate insights of and for local governments and that questions had been developed by researchers from various listed universities. The email directed participants to a FAQ on the CivicPulse web site that explained that information will be de-identified for distribution.

Participants gave their consent by clicking to the survey. CivicPulse has a mission to enhance local governance through shared data and research, and it regularly releases reports to participating government officials with findings from its surveys.

The vignette experiment did not involve deception; it asked participants to imagine themselves within a hypothetical scenario (Appendix C). Subsequent open-ended questions allowed participants to elaborate on their responses and comment on the vignette's applicability to their own communities. A total of 818 elected officials viewed the module on water infrastructure that included the experiment; of the 699 who answered the module's first question, 657 responded to the vignette, for a 6% attrition rate. Testing confirms that treatment assignment does not predict attrition in question response (Appendix F).

The upper section of Table A1 reports descriptive information provided by CivicPulse about the respondents who viewed the water module. The municipal and township officials (84% of the sample) are from cities that are somewhat larger and more urban than the typical city, although the sample mean for city population size is inflated by one observation from a very large city; omitting that observation, the sample mean is 23,564. Responding county officials (16%) are from jurisdictions that closely resemble counties nationwide.

To protect respondents' confidentiality, CivicPulse does not provide their specific jurisdictions in the data release, sharing only the terciles that a respondent's jurisdiction falls into for population, urbanicity, education, and county-level presidential vote. We use these terciles in our analyses. We do not include county-level vote because of the mismatch in geographic scale, but all results are robust to its inclusion.

The lower section of Table A1 reports demographic and personal information provided by survey respondents. Although demographic information about the population of local elected officials nationwide is not known, our sample is generally consistent with findings about who runs for office (Motel 2014).

The columns marked as Sample in the lower section are for the full set of elected officials who responded to the vignette, who come from 49 states. Data on personal characteristics are missing for over a quarter of respondents, mostly from the portion of the sample who viewed an additional long survey module on an unrelated topic after the water module. The columns marked as complete case are for the set of 375 respondents who did not see the additional module and have complete data for the covariates specified in the PAP for the interaction model described in the article's main text. Respondents in the complete-case sample come from 45 states and, as Table A1 shows, closely resemble the larger sample.

C. Vignette and variable measurement

All measurement decisions are consistent with those specified in the PAP.

Variable	Question wording	Measurement	Notes
News treatment	<p>Imagine yourself in the following scenario. A consultant hired by your local government recommends an overdue pipe replacement project to address recent water main breaks [-- / featured prominently in the local newspaper].</p> <p>The current average household water rate is \$30 per month, which is typical for your region. The project recommended by the consultant would be funded with a revenue bond, requiring an increase of an additional \$10 per month, so the new rate would be \$40 per month.</p>	<p>control [0] treatment [1]</p>	
Investment support	<p>With only this information, how likely or unlikely are you to support the bond?</p>	<p>very unlikely [0] unlikely [.25] neither likely nor unlikely [.5] likely [.75] very likely [1]</p>	
Competition	<p>When you last ran for office, did you face an opponent in the general election?</p>	<p>yes [1] no [0] other: ____ [.]</p>	<p>Results are robust to including respondents indicating “other,” all scored either as 0 or as 1.</p>
Ambition	<p>How would you characterize your interest in holding a higher elected office in the future?</p>	<p>I have no interest in holding higher elected office at any time in the future. [0] I am open to the possibility of holding higher elected office in the future. [1] I am actively considering running for higher elected office. [1]</p>	<p>Because the latter two responses are difficult to distinguish conceptually, we combined them to measure ambition as a binary variable.</p>

Partisanship	<p>Generally speaking, do you usually think of yourself as a</p> <p>Democrat Republican Independent Other party (please specify): _____</p> <p>[If neither Democrat nor Republican are selected:] Do you think of yourself as closer to the Democratic Party or the Republican Party?</p> <p>Democratic Party Republican Party Neither</p>	<p><i>Democrat:</i> Democrat [1] Democratic Party [1] all other [0]</p> <p><i>Republican:</i> Republican [1] Republican Party [1] all other [0]</p>	
College graduate	What is the last grade of school you completed?	<p>Less than high school [0] High school graduate [0] Technical/trade school [0] Some college [0] College graduate [1] Some graduate school [1] Graduate degree [1]</p>	
Population	The total number of residents living in the given geographic unit, from the 2015 American Community Survey.	<p>< 2,650 (33 pct.) [0] > 2,650 and < 10,100 (66.7 pct.) [.5] > 10,100 [1]</p>	Available only in terciles to protect respondents' confidentiality.
County	A variable indicating the government position of the respondent.	<p>County [1] Municipality [0] Township [0]</p>	
Female	What is your sex?	<p>Male [0] Female [1]</p>	Missing data filled in by CivicPulse using probabilistic name-based gender coding.
White, non-Hispanic	<p>Are you of Hispanic, Latino, or Spanish origin?</p> <p>No, not of Hispanic, Latino, or Spanish origin Yes, Mexican, Mexican Am., Chicano Yes, Puerto Rican Yes, Cuban</p>	<p>Non-Hispanic and White [1] all other [0]</p>	

	<p>Yes, another Hispanic, Latino, or Spanish origin</p> <p>Which of the following best describes your race/ethnicity? Please check all that apply.</p> <p>White Black/African American Asian/Asian American (includes East Asian, South Asian, Southeast Asian, and Pacific Islander) Native American Other (please specify): ____</p>		
Ideology	In general, do you think of yourself as:	<p>Very conservative [0] Somewhat conservative [.25] Moderate, middle of the road [.5] Somewhat liberal [.75] Very liberal [1] Not sure [.]</p>	
% college grad	% of 25-years-or-older residents in the given geographic unit who have completed a 4-year, post-secondary degree, taken from 2015 American Community Survey.	<p>< 16.8% (33 pct.) [0] > 16.8% and < 26.6% (66.7 pct.) [.5] > 26.6% [1]</p>	Available only in terciles to protect respondents' confidentiality.
Urban	% of residents in the given geographic unit who reside in an urban area, taken from the 2010 Census.	<p>< 11.4% (33 pct.) [0] > 11.4% and < 95.9% (66.7 pct.) [.5] > 95.9% [1]</p>	Available only in terciles to protect respondents' confidentiality.
Household income	The median household income in the given geographic unit, taken from the 2015 American Community Survey.	<p>< \$45,976 (33 pct.) [0] > \$45,976 and < \$61,250 (66.7 pct.) [.5] > \$61,250 [1]</p>	Available only in terciles to protect respondents' confidentiality.
Region	Census-designated regions.		Constructed by authors using state identifiers.
Drinking water concern	How concerned, if at all, are you about the condition of drinking water infrastructure in your own community?	<p>not at all concerned [0] slightly concerned [.25] moderately concerned [.5] very concerned [.75] extremely concerned [1]</p>	

D. Balance between control and treatment groups

	Complete Case		Imputed	
	Control	Treatment	Control	Treatment
Elected official:				
Democrat or lean Democrat	35%	42%	31%	43%***
Republican or lean Republican	54%	50%	57%	46%**
College graduate	65%	69%	60%	67%
White, non-Hispanic	90%	85%	86%	86%
Female	31%	31%	31%	31%
Electoral competition	59%	65%	62%	63%
Ambition	90%	88%	89%	88%
City or county:				
Population (3-category)	0.63	0.64	0.63	0.63
% college graduate (3-category)	0.66	0.65	0.62	0.62
% urban (3-category)	0.60	0.68**	0.62	0.64
Household income (3-category)	0.57	0.53	0.56	0.52
County	16%	15%	17%	14%
N	172	203	313	344

Table A2. Balance between control and treatment groups. * $p < .1$, ** $p < .05$, *** $p < .01$.

Assignment to the news treatment was not balanced on all measured covariates; importantly, members of the treatment group disproportionately identified as Democrats. Imbalance on partisanship was more pronounced in the full sample than in the sample that viewed the water module only, and the imbalance persisted in the imputed data. (As described in Appendix H, we incorporated interactions between partisanship and survey instrument in our imputation model.) In contrast, imbalance on urbanicity was evident only in the sample that received the shorter survey.

To judge whether observed covariate imbalances are larger than would be expected by chance alone, we calculated Wald statistics from permutation tests regressing the treatment indicator on the PAP-specified covariates for the complete-case sample and an averaged imputed sample (Gerber and Green 2012). Results are depicted in Figure A1. For the complete-case sample, we clearly fail to reject the null hypothesis that all coefficients are zero; imbalance is more evident in the imputed sample, perhaps because of uneven attrition.

All results in the main text are from models that control for covariates specified in the PAP and their interactions with the news treatment: partisanship and education of the elected official, and population and government type of the city or county. Results are robust to including the entire set of available covariates and interactions in the estimation models (Model (6) in Appendix G and I). As shown in Figure A2, the pattern of results is evident within partisan subgroups, estimated separately.

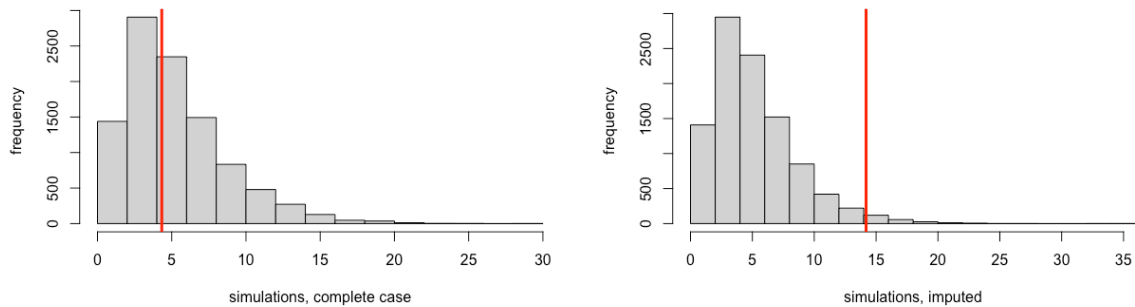


Figure A1. Distributions of Wald statistics (10,000 permutations) under the null hypothesis of no relation between treatment and a PAP-specified covariate for complete case and imputed samples. Permutation tests of covariate balance produce $p=.53$ for the complete case sample and $p=.02$ for the imputed sample.

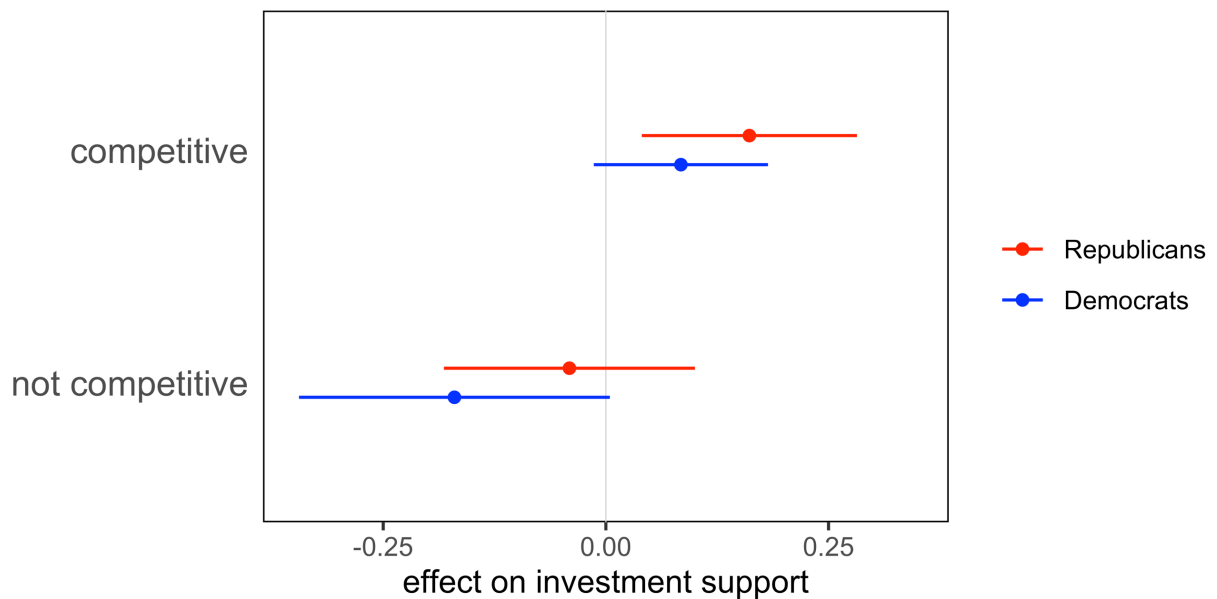


Figure A2. Marginal effect of news coverage on predicted support for infrastructure investment, by electoral competition and estimated in separate analyses for Republicans ($N=193$) and for Democrats ($N=145$), using the complete-case sample. Differences between competition subgroups are significant at $p<.01$ for Democrats and $p<.07$ for Republicans.

E. Investment support, distribution and raw data

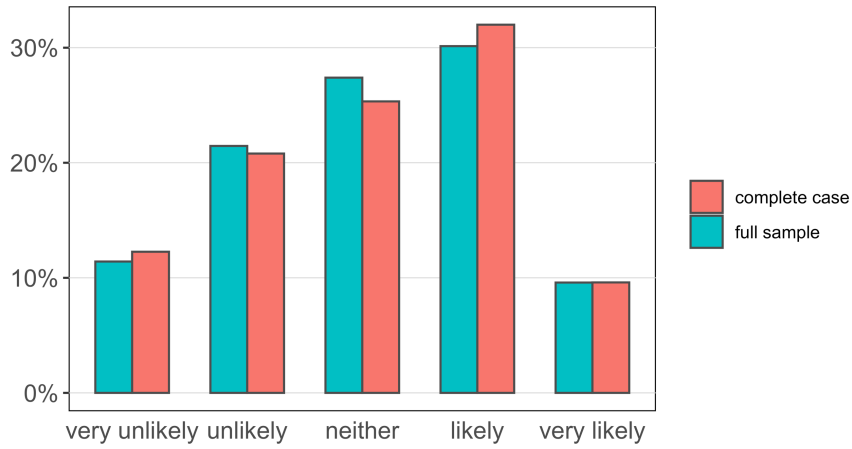


Figure A3. Distribution of support for infrastructure investment among the full sample of survey respondents (N=657) and the complete case sample (N=375).

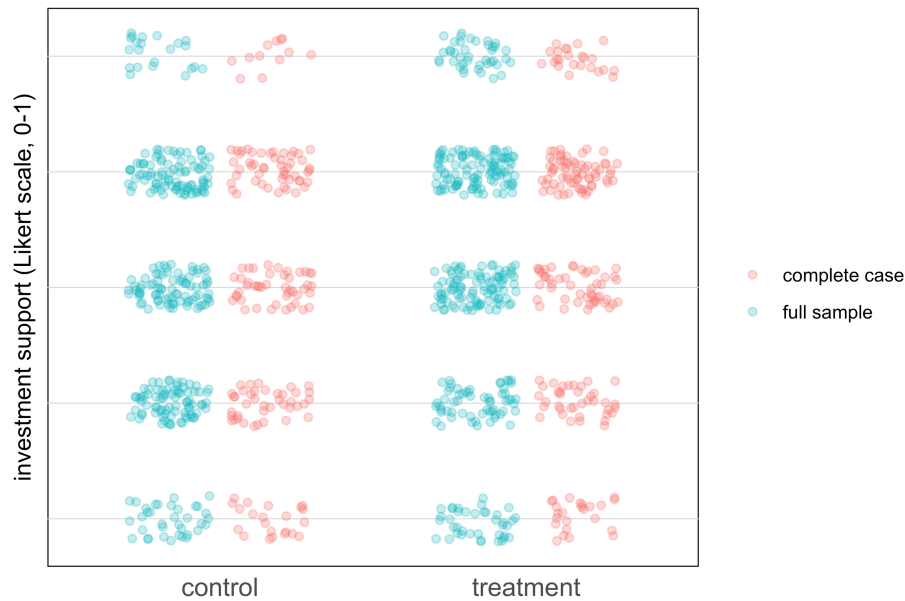


Figure A4. Support for infrastructure investment by experimental group among the full sample of survey respondents (N=657) and the complete case sample (N=375).

F. Attrition on outcome measure

	Sample		Complete case	
News treatment	-0.011 (0.018)	-0.008 (0.018)	-0.011 (0.010)	-0.010 (0.009)
Drinking water concern		-0.046* (0.028)		-0.024** (0.012)
Population		-0.030 (0.024)		-0.018 (0.013)
County		0.025 (0.028)		0.016 (0.016)
Intercept	0.068*** (0.014)	0.092*** (0.022)	0.015* (0.009)	0.029* (0.017)
Adj. R-sq.	0.001	0.006	0.003	0.095
N		699		434
Attrition		6%		<1%

Table A3. Predicting attrition on outcome measure. Models estimate missingness on vignette response among respondents who answered the survey's first question. OLS coefficients with robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ (two-tailed).

Response rates for the vignette were very high. In the full sample, only 6% of those who answered the module's first question on concern about the condition of drinking water infrastructure in their own community did not respond to the vignette. Among the group that saw the water module only, attrition on this second question was less than 1%. Assignment to treatment did not predict attrition on the outcome variable for either group. Those who expressed higher levels of drinking water concern were more likely to remain for the vignette. Our results are robust to controlling for drinking water concern and its interaction with the news treatment (Model (6) in Appendix G and I).

G. Complete case data: PAP specifications and additional controls

Table A4 shows results across multiple model specifications using complete-case data for respondents who received a survey that included only the drinking water module. The specifications match those for the multiple imputation results reported in Table A7 (Appendix I). Complete-case results reported in Figures 1 and 2 of the main text are from Models (2) and (5) below. Consistent with the PAP, all analyses use unweighted survey responses.

Columns (1) and (2) show analyses outlined in the preregistered analysis plan (PAP) for testing the direct effect of the news treatment. Columns (3) and (4) show the PAP-specified analysis testing the competition and ambition hypotheses in separate models. The fifth column (5) is our preferred model that includes both competition and ambition in the same specification, along with interactions for all the PAP-specified control variables. Model (6) includes interactions for the complete set of available controls, including response to the survey's first question about drinking water concern. Results differ little across these specifications.

	(1) PAP: Direct effect, no controls	(2) PAP: Direct effect, controls	(3) PAP: competition	(4) PAP: ambition	(5) PAP variables, complete interactions	(6) Additional controls and interactions
News treatment	0.059** (0.028)	0.055* (0.029)	-0.079 (0.049)	0.086 (0.088)	0.024 (0.149)	-0.133 (0.203)
Competition			-0.127*** (0.044)		-0.140*** (0.044)	-0.126*** (0.045)
News * competition			0.202*** (0.062)		0.231*** (0.066)	0.228*** (0.067)
Ambition				0.010 (0.067)	0.072 (0.070)	0.082 (0.075)
News * ambition				-0.037 (0.094)	-0.107 (0.095)	-0.105 (0.101)
Democrat		0.042 (0.054)	0.027 (0.054)	0.051 (0.055)	0.041 (0.071)	0.032 (0.076)
News * Democrat					-0.006 (0.110)	-0.062 (0.118)
Republican		-0.072 (0.053)	-0.091* (0.055)	-0.068 (0.054)	-0.132* (0.072)	-0.166** (0.080)
News * Republican					0.058 (0.112)	0.156 (0.120)
College graduate		0.018 (0.033)	0.009 (0.033)	0.012 (0.033)	0.002 (0.044)	0.012 (0.046)
News * college grad					0.007 (0.066)	0.000 (0.068)
Population		-0.087** (0.041)	-0.092** (0.043)	-0.083** (0.041)	-0.003 (0.057)	0.105 (0.077)
News * population					-0.172** (0.085)	-0.218** (0.106)
County		0.027 (0.044)	0.034 (0.044)	0.026 (0.045)	-0.134** (0.066)	-0.164** (0.079)

News * county					0.310***	0.280***
					(0.089)	(0.104)
Female						0.061
						(0.046)
News * female						-0.092
						(0.068)
White, non-Hispanic						-0.038
						(0.081)
News * white NH						0.059
						(0.105)
Ideology (liberal)						-0.113
						(0.111)
News * liberal						0.382**
						(0.163)
% college grad						0.043
						(0.069)
News * % college grad						-0.001
						(0.099)
Urban						-0.096
						(0.079)
News * urban						-0.043
						(0.103)
Household income						0.043
						(0.064)
News * income						-0.007
						(0.095)
West						-0.143*
						(0.073)
News * West						0.173
						(0.106)
South						-0.048
						(0.065)
News * South						0.017
						(0.087)
Northeast						0.001
						(0.057)
News * northeast						0.051
						(0.079)
Drinking water concern						0.132
						(0.083)
News * concern						-0.045
						(0.108)
Intercept	0.485***	0.546***	0.649***	0.535***	0.584***	0.586***
	(0.021)	(0.056)	(0.063)	(0.085)	(0.104)	(0.154)
N	430	395	378	392	375	363
R2 Adj.	0.008	0.042	0.056	0.038	0.077	0.107

Table A4. Estimated treatment effects using listwise deletion with the sample that received the drinking water survey module only. OLS coefficients with robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ (two-tailed).

H. Multiple imputation

Elected official:	
Democrat or lean Democrat	24%
Republican or lean Republican	24%
College graduate	21%
White, non-Hispanic	23%
Female	1%
Ambition	25%
Electoral competition	27%
Investment support	0%
City or county:	
Population (3-category)	0%
% college graduate (3-category)	0%
% urban (3-category)	0%
Household income (3-category)	0%
County	0%
N	657

Table A5. Missingness on covariates in the full sample.

As shown in Table A5, data on elected officials' personal characteristics are missing for a large portion of respondents who did not respond to the standard content at the end of the survey. (CivicPulse provides gender estimated using a first-name algorithm.) Table A6 shows the predictors of missingness of the full set of PAP-specified covariates. Treatment does not predict missingness, but missingness is related with the outcome variable for respondents who received both survey modules. Listwise deletion of cases from the full sample that have missing data could therefore bias our estimates of treatment effects. There also is a large known, random component to the missingness: just over one-third of respondents were selected to receive an additional long survey module on an unrelated topic after the water module, and they account for nearly all of the cases with missing data. Among those who viewed only the water module, just 1% (6 respondents) did not complete any of the standard survey content, and non-completion was only weakly related to any measured characteristic.

	Sample	Both modules	Water module only
News treatment	-0.004 (0.024)	-0.048 (0.065)	0.005 (0.012)
Investment support	-0.123*** (0.042)	-0.403*** (0.115)	0.009 (0.025)
Second module	0.521*** (0.033)		
Population (3-category)	0.004 (0.041)	0.033 (0.112)	-0.008 (0.016)
% college grad (3-category)	-0.014 (0.039)	0.016 (0.108)	-0.028 (0.019)
% urban (3-category)	0.004 (0.042)	-0.093 (0.121)	0.033* (0.018)
Household income	0.077** (0.037)	0.158 (0.108)	0.034* (0.019)
% county GOP vote share (3-category)	0.019 (0.036)	0.131 (0.102)	-0.017 (0.015)
County	-0.039 (0.040)	-0.110 (0.113)	-0.002 (0.009)
West	-0.076** (0.038)	-0.190** (0.094)	-0.005 (0.019)
South	0.055 (0.034)	0.132 (0.086)	0.006 (0.016)
Northeast	0.033 (0.030)	0.105 (0.091)	0.000 (0.014)
Intercept	0.031 (0.048)	0.646*** (0.135)	-0.005 (0.022)
N	656	227	429
R ² Adj.	0.407	0.075	-0.002
% missing	19%	54%	1%

Table A6. Predicting missingness on all PAP-specified covariates (ambition, competition, partisanship and education). OLS coefficients with robust standard errors in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$ (two-tailed).

We addressed the missing data problem in two ways. First, we restricted our complete-case analysis using listwise deletion to the sample of respondents who viewed only the water infrastructure module, minimizing the impacts of attrition. Second, to maximize statistical power and avoid any bias that may result from omitting observations, we used multiple imputation with chained equations to fill in missing covariate values on the full sample. Under conditions of covariate data missing partly at random, multiple imputation improves precision in estimates of treatment effects and may reduce bias (King et al. 2001; Arel-Bundock and Pelc 2018).

We carried out the imputations using the `mice` package (van Buuren and Groothuis-Oudshoorn 2011), implemented in R version 4.0.4. We imputed 20 complete datasets, including as predictors in the imputation model our outcome measure, all covariates in the complete control analysis, interactions, and a variable indicating receipt of the second survey module. We adjusted the prediction matrix to avoid excessive influence by components of the interactions. We report results using imputations calculated using predictive mean matching; imputing binary

variables with logistic regression and varying the prediction matrix produced nearly identical results. Figure A5 shows the distributions of observed (in blue) and imputed (in red) covariate values. The imputations produced closed matches with the observed distributions in the full sample of survey respondents.

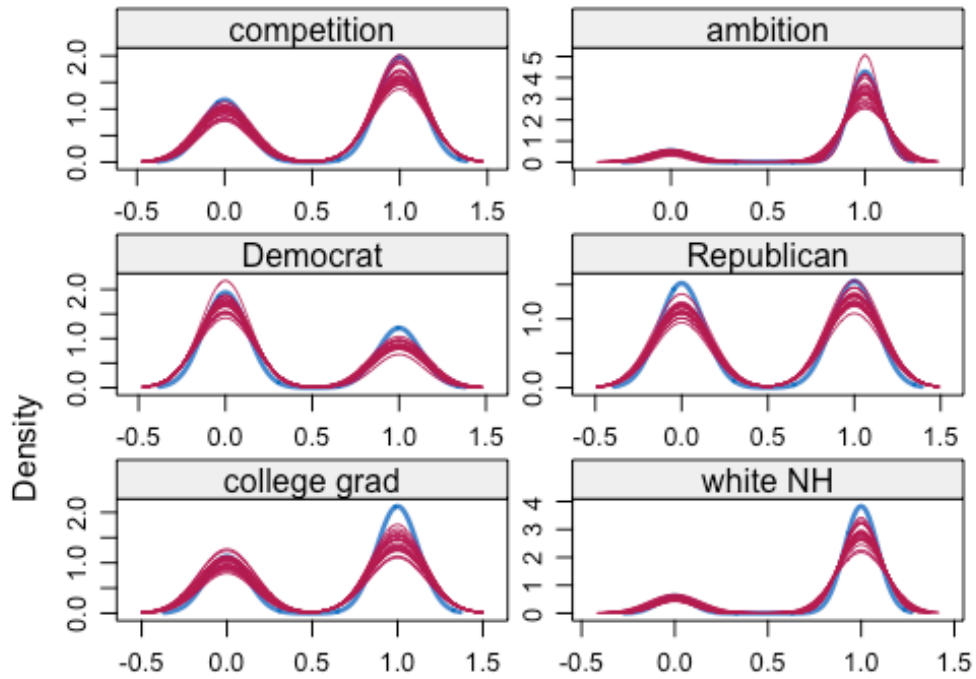


Figure A5. Density plots of observed (in blue) and imputed (in red) covariate values.

I. Imputed data: PAP specifications and additional controls

Table A7 shows results across multiple model specifications using data from the full set of respondents to the experimental vignette, with missing covariate data filled in using multiple imputation through procedures outlined in Appendix H. The specifications match those for the complete-case results reported in Table A4 (Appendix G). Multiple imputation results reported in Figures 1 and 2 of the main text are from Models (2) and (5) below. Consistent with the PAP, all analyses use unweighted survey responses.

Columns (1) and (2) show analyses outlined in the PAP for testing the direct effect of the news treatment. Columns (3) and (4) show the PAP-specified analysis testing the competition and ambition hypotheses in separate models. The fifth column (5) is our preferred model that includes both competition and ambition in the same specification, along with interactions for all the PAP-specified control variables. Model (6) includes interactions for the complete set of available controls, including response to the survey's first question about drinking water concern. Results differ little across these specifications.

	(1) PAP: Direct effect, no controls	(2) PAP: Direct effect, controls	(3) PAP: competition	(4) PAP: ambition	(5) PAP variables, complete interactions	(6) Additional controls and interactions
News treatment	0.051** (0.023)	0.041* (0.023)	-0.035 (0.039)	0.037 (0.073)	0.025 (0.117)	-0.110 (0.148)
Competition			-0.094** (0.039)		-0.098** (0.039)	-0.091** (0.040)
News * competition			0.122** (0.051)		0.132** (0.054)	0.138** (0.056)
Ambition				0.031 (0.055)	0.043 (0.057)	0.041 (0.060)
News * ambition				0.005 (0.078)	-0.018 (0.081)	-0.020 (0.084)
Democrat		0.036 (0.042)	0.031 (0.042)	0.039 (0.042)	0.046 (0.060)	0.037 (0.063)
News * Democrat					-0.024 (0.092)	-0.069 (0.097)
Republican		-0.060 (0.042)	-0.069 (0.043)	-0.059 (0.042)	-0.066 (0.059)	-0.060 (0.062)
News * Republican					-0.013 (0.090)	0.018 (0.092)
College graduate		0.006 (0.026)	0.004 (0.026)	0.005 (0.027)	0.011 (0.036)	0.018 (0.037)
News * college grad					-0.019 (0.055)	-0.028 (0.055)
Population		-0.069** (0.031)	-0.065** (0.033)	-0.069** (0.032)	-0.025 (0.046)	-0.002 (0.058)
News * population					-0.076 (0.066)	-0.048 (0.081)
County		0.006 (0.033)	0.008 (0.033)	0.005 (0.033)	-0.073 (0.045)	-0.070 (0.056)
News * county					0.162** (0.066)	0.136* (0.078)

Female						0.046 (0.036)
News * female						-0.074 (0.051)
White, non-Hispanic						0.014 (0.055)
News * white NH						0.019 (0.075)
Ideology (liberal)						-0.017 (0.096)
News * liberal						0.262* (0.142)
% college grad						-0.009 (0.050)
News * % college grad						0.072 (0.074)
Urban						-0.004 (0.058)
News * urban						-0.083 (0.078)
Household income						-0.015 (0.049)
News * income						0.015 (0.071)
West						-0.092* (0.052)
News * West						0.071 (0.076)
South						-0.056 (0.043)
News * South						0.063 (0.060)
Northeast						0.019 (0.043)
News * northeast						0.042 (0.060)
Drinking water concern						0.101 (0.067)
News * concern						-0.061 (0.086)
Intercept	0.486*** (0.016)	0.547*** (0.044)	0.609*** (0.051)	0.518*** (0.065)	0.552*** (0.078)	0.528*** (0.102)
N	657	657	657	657	657	657
Imputations		20	20	20	20	20
R2 Adj.	0.006	0.032	0.043	0.031	0.047	0.066

Table A7. Estimated treatment effects using multiple imputation to fill in missing covariate values in the full sample, including those who received both survey modules. OLS coefficients with robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ (two-tailed).

J. Complete case with full sample

Table A8

shows results when using the full sample described in Appendix H and treating missing data using listwise deletion. The first column (1) shows the direct effect of news treatment estimated for all respondents, as reported in the first column of Table A7. After controlling for variables identified in the PAP (2), the effect size diminishes by 40%, but listwise deletion also drops one-quarter of the respondents. The sample of cases without missing data shrinks further when including competition and ambition, as shown in column (3). Column (4) shows the same model as column (1), estimated only for complete cases. Comparing the coefficient in column (4) with column (1), and additionally with results in Appendix G for the sample receiving the water module only, makes evident that bias in attrition among those who received a survey with multiple modules accounts for a large part of the reduction in the estimate of the main effect.

Figure A6 shows results using listwise deletion on the full set of respondents exposed to different survey instruments, along with results reported in the main text. The estimate of the overall effect of the news treatment is smaller than those estimated with other sample constructions and not significant, but the estimated effect for politicians in electorally competitive contexts is similar.

	(1) No controls	(2) PAP: Direct effect, controls	(3) PAP variables, complete interactions	(4) No controls with interactions sample
News treatment	0.051** (0.023)	0.031 (0.026)	0.033 (0.131)	0.034 (0.027)
Competition			-0.116*** (0.040)	
News * competition			0.182*** (0.059)	
Ambition			0.059 (0.062)	
News * ambition			-0.042 (0.086)	
Democrat		0.047 (0.046)	0.060 (0.062)	
News * Democrat			-0.050 (0.096)	
Republican		-0.054 (0.045)	-0.067 (0.064)	
News * Republican			-0.020 (0.098)	
College graduate		0.011 (0.029)	0.003 (0.041)	
News * college grad			-0.016	

Population		-0.095***	(0.059)	
		(0.036)	-0.027	(0.056)
News * population			-0.129	(0.080)
County		0.000	-0.116**	(0.055)
		(0.038)		
News * county			0.224***	(0.079)
Intercept	0.486***	0.575***	0.576***	0.506***
	(0.016)	(0.048)	(0.089)	(0.020)
N	657	497	463	463
R2 Adj.	0.006	0.036	0.054	0.001

Table A8. Estimated treatment effects using listwise deletion with the full sample, including those who received both survey modules. OLS coefficients with robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ (two-tailed).

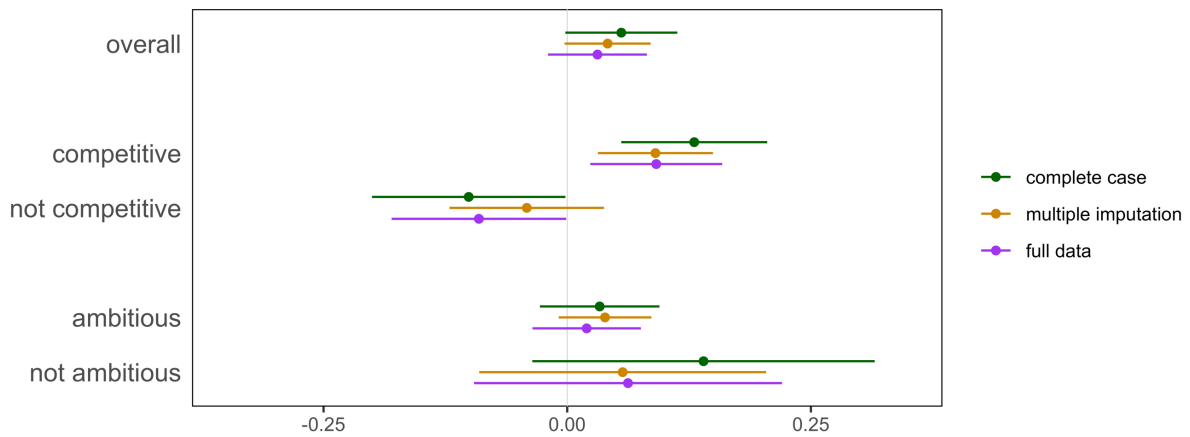


Figure A6. Effect of news coverage by electoral competition and ambition across sample constructions. Full data estimates come from Models (2) (overall effect) and (3) in Table A8. Bars show 95% confidence intervals.

K. Alternative missing data procedures

Table A9 and Figure A7 show results for the overall effect of news treatment when using alternative procedures for handling missing values on partisanship, the PAP-specified covariate with imbalance in treatment assignment. In the first two columns, we construct an interval estimate of the treatment effect by setting all missing covariate values to their minimum and maximum levels. The models also include controls for population and county, the other PAP-specified variables that did not have missing data. The method produces an overall treatment effect estimate in the range of 0.16 to 0.2, effects that are statistically significant with 95% confidence throughout almost the entire range of estimates.

In models (3) and (4), we substitute missing data on partisanship with mean values for proportion Democrat and proportion Republican in the observed data. In model (4), we follow the guidance of Gerber and Green (2012) by also including a missingness dummy as an additional covariate as well as interactions between treatment and all other included variables. All of these approaches produce substantive effects that are very similar with p -values of less than 0.7.

	(1) Treating all MD as Democrats	(2) Treating all MD as Republicans	(3) Substituting MD with mean value	(4) Substituting MD with mean value
News treatment	0.049** (0.023)	0.041* (0.022)	0.043* (0.022)	0.076 (0.083)
Democrat, MDs = Dem	-0.018 (0.042)			
Republican, MDs = Dem	-0.063 (0.044)			
Democrat, MDs = Rep		0.039 (0.044)		
Republican, MDs = Rep		-0.071* (0.042)		
Democrat, MDs = mean			0.039 (0.044)	0.069 (0.057)
Republican, MDs = mean			-0.062 (0.044)	-0.044 (0.056)
MD: partisanship				-0.090** (0.036)
Population	-0.062** (0.031)	-0.068** (0.031)	-0.067** (0.031)	-0.045 (0.044)
County	-0.006 (0.033)	0.002 (0.033)	0.002 (0.033)	-0.076* (0.044)
News * Democrat				-0.055 (0.088)
News * Republican				-0.045 (0.088)
News * MD: partisanship				0.043

				(0.052)
News * population				-0.042
				(0.062)
News * county				0.158**
				(0.065)
Intercept	0.561***	0.566***	0.548***	0.550***
	(0.042)	(0.042)	(0.042)	(0.054)
N	657	657	657	657
R2 Adj.	0.015	0.039	0.029	0.041

Table A9. Estimated overall treatment effects using alternative procedures for handling missing data on partisanship. OLS coefficients with robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ (two-tailed).

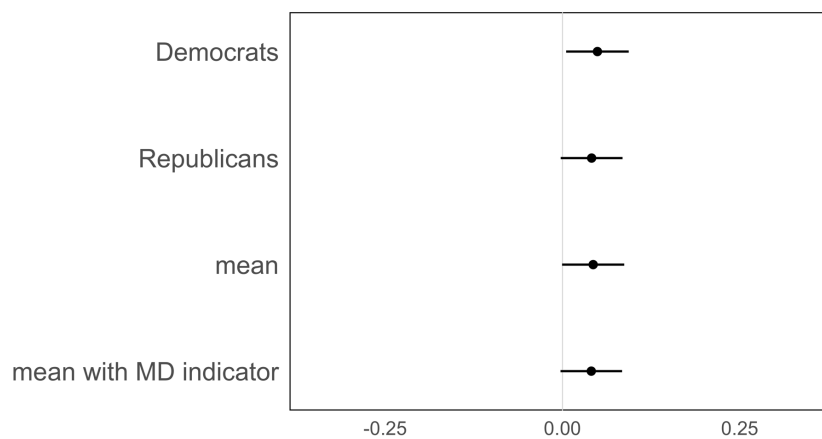


Figure A7. Overall effect of news coverage using alternative procedures for handling missing data on partisanship. Estimates come from Table A7. Bars show 95% confidence intervals.

L. Predictors of electoral competition

News treatment	0.038 (0.051)
Ambition	0.248*** (0.081)
Democrat	-0.020 (0.096)
Republican	-0.040 (0.097)
College graduate	-0.068 (0.056)
Population	0.254*** (0.087)
County	-0.040 (0.081)
Female	-0.006 (0.056)
White, non-Hispanic	-0.072 (0.074)
Ideology (liberal)	0.038 (0.130)
% college grad	0.025 (0.087)
Urban	0.003 (0.091)
Household income	-0.016 (0.077)
West	0.144* (0.078)
South	0.127* (0.067)
Northeast	-0.019 (0.068)
Intercept	0.292* (0.149)
N	363
R2 Adj.	0.062

Table A10. Predicting electoral competition estimated with listwise deletion, using the complete-case sample. OLS coefficients with robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ (two-tailed).

As demonstrated in column (6) of Table A4, results are robust to controlling for all of these characteristics and their interactions with the news treatment.

M. Consistency in electoral competition across elections

	All (9) States		Omitting Louisiana	
	Contested, lag	Uncontested, lag	Contested, lag	Uncontested, lag
Contested	3,037	1,372	2,324	1,082
	72%	33%	67%	28%
Uncontested	1,159	2,735	1,159	2,735
	28%	67%	33%	72%
Total	4,196	4,107	3,483	3,817
	100%	100%	100%	100%

Table A11. Contestation in mayoral elections, by contestation in previous election. Data collected by the Local Elections in America Project (LEAP) from nine states over the period 2000-2017 and provided to the authors by Melissa Marschall. States included: CA, CT, IN, KY, LA, MN, RI, VA, WA. Contestation is measured at the first stage election that is capable of producing a winner. In Louisiana, contestation is measured for the primary, as unopposed candidates do not appear on the general election ballot. For more information on LEAP data, see Marschall, Lappie, and Williams (2017).

N. Binary modeling of outcome measure

	Complete case	Imputed
News treatment	-0.084 (0.235)	-0.059 (0.188)
Competition	-0.197*** (0.076)	-0.160*** (0.060)
News * competition	0.343*** (0.108)	0.217** (0.092)
Ambition	0.173 (0.121)	0.106 (0.091)
News * ambition	-0.146 (0.164)	-0.010 (0.128)
Democrat	0.014 (0.123)	0.084 (0.109)
News * Democrat	0.060 (0.180)	-0.020 (0.153)
Republican	-0.165 (0.115)	-0.048 (0.096)
News * Republican	0.057 (0.176)	-0.077 (0.144)
College graduate	0.000 (0.077)	0.037 (0.062)
News * college grad	0.063 (0.111)	-0.011 (0.090)
Population	-0.026 (0.099)	-0.076 (0.075)
News * population	-0.118 (0.142)	-0.001 (0.108)
County	-0.196* (0.100)	-0.171** (0.069)
News * county	0.368** (0.146)	0.255** (0.107)
Intercept	0.464*** (0.163)	0.418*** (0.130)
N	375	657
Imputations		20
R2 Adj.	0.041	0.045

Table A12. Estimated treatment effects using a linear probability model, coding “likely” and “very likely” in the outcome measure as 1, and all other responses as 0. OLS coefficients with robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ (two-tailed).

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