Supplemental Information

The Supplemental Information contains two key sections. In the first section, entitled "Study Descriptions and Question Wordings," we present the vignettes and questions used in the studies we describe in the main paper. In the second section, entitled "Supplemental Analyses," we present the models underlying each of the figures we present in the main paper as well as alternative specifications and sensitivity analyses, where appropriate. Each subsection of the "Supplemental Analyses" section is preceded by an explanation of our analytical procedures and the contents presented therein.

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Study Descriptions and Question Wordings

In this section, we provide descriptions of how we fielded the surveys in which our experiments were embedded and the vignette and question wordings for each of our experiments.

In Footnote 10, we briefly discuss the formulation of our control conditions. We elaborate on that discussion here. Including control conditions in survey experiments is important so that researchers can assess not only the relative effects of the treatment conditions, but also the effects of each treatment relative to the absence of any treatment (Gaines, Kuklinski, and Quirk 2007). One of two general types of control conditions could be suitable for setting: a condition in which the elected executive offers a public statement, or a condition in which the executive does not make a statement. Each type of control condition describes a plausible real-world scenario to which the effects of blame claiming and blame deflecting could be compared. In the former case, the control focuses on the point at which an executive offers a public response to a crisis, such that our treatment effects indicate the effects of blame claiming and blame deflecting conditional on the executive offering a public response. In the latter case, the control represents the period between the crisis occurring and the elected executive offering a public response, such that our treatment effects indicate the effects of blame claiming and blame deflecting when compared to the executive's lack of response.

In our four governmental crisis studies, we use the former control condition in which the elected executive offers a public statement. This type of control condition offers two advantages. First, by having the executive make a statement, our control condition differs from each treatment only with respect to the executive's comments concerning blame, enabling us to attribute the observed effects to the executive's claiming or deflecting blame. Second, because citizens have a bias for action versus inaction in the face of policy problems or crises (Miller and Reeves 2017; Olsen 2017), our control facilitates a hard test for our theory because it establishes higher baseline favorability of the executive among respondents in the control condition than would a control condition in which the executive did not offer a response, making it more difficult to recover positive effects of blame claiming or blame deflecting.

In our Flint study, we use the latter type of control condition in which the elected executive does not offer a response. This control condition reflects how elected executives sometimes respond to blame by "keeping a low profile" and hoping that public attention to the crisis will dissipate (Hood 2011, 43-47). Thus, while this control makes it more difficult to determine whether the treatment effects we observe, since the treatments differ from the control both in terms of offering a response and the content of that response, it represents a common, real-world scenario in which executives avoid offering public comments—sometimes only for a short length of time after the crisis, but other times for extended periods.

We consistently find that blame claiming is an effective presentational strategy in the face of a governmental crisis irrespective of which control condition we use as a baseline, suggesting that the public responds more favorably to blame claiming than to offering perfunctory responses or avoiding making a public statement.

Flood Study

Study Description

We fielded our flood study on the January 2018 wave of The American Panel Survey, a nationally representative panel survey administered monthly by GfK/Knowledge Networks on behalf of the Weidenbaum Center at Washington University in St. Louis. The January 2018 wave included 1963 respondents, 1945 of which provided responses to at least one of our key outcome measures. Vignette wording is displayed in Table 1, and post-treatment question wording is provided below.

Question Wording

- Do you approve or disapprove of the mayor's handling of the flood?
  - Strongly approve
  - Somewhat approve
  - Somewhat disapprove
  - Strongly disapprove
  - Don't know
- How likely would you be to vote for the mayor in the next election?
  - Very likely
  - Somewhat likely
  - Somewhat unlikely
  - Very unlikely
  - Don't know
- How would you assign blame for the flood mentioned above? The total cannot exceed 100.
  - President
  - US Congress
  - Federal Emergency Management Agency
  - State governor
  - Mayor
  - City council
  - City's emergency management agency
  - Other
- Thinking about the mayor mentioned above, how well do you think the following traits describe him? intelligent; provides strong leadership; honest; competent; trustworthy.
  - Not well at all (1)
  - Slightly well (2)
  - Moderately well (3)

– Very well (4)
– Extremely well (5)
– Not sure

Bridge Collapse Study

Study Description

We fielded our bridge collapse study on Amazon's Mechanical Turk (MTurk) on October 18, 2017. We recruited 1006 respondents, 878 of which passed our attention check and provided responses to at least one of our key outcome measures.[37] Vignette wording is displayed in Table 1, and post-treatment question wording is provided below.

Question Wording

- Do you approve or disapprove of the governor's handling of the bridge collapse?
  - Strongly approve
  - Somewhat approve
  - Somewhat disapprove
  - Strongly disapprove
- How likely would you be to vote for the governor in the next election?
  - Very likely
  - Somewhat likely
  - Somewhat unlikely
  - Very unlikely
- How would you assign blame for the bridge collapse mentioned above? The total cannot exceed 100.
  - President
  - US Congress
  - US Department of Transportation
  - State governor
  - State legislature
  - State department of transportation
  - Other
- Thinking about the governor mentioned above, how well do you think the following traits describe him? intelligent; provides strong leadership; honest; competent; trustworthy.
  - Not well at all (1)
  - Slightly well (2)
  - Moderately well (3)
  - Very well (4)
  - Extremely well (5)

Budget Shortfall Study

Study Description

We fielded our budget shortfall study on Amazon's Mechanical Turk (MTurk) on October 18, 2017. We recruited 1006 respondents, 879 of which passed our attention check and provided responses to at least one of our key outcome measures. Vignette wording is displayed in Table 1, and post-treatment question wording is provided below.

Question Wording

- Do you approve or disapprove of the governor's handling of the budget shortfall?
  - Strongly approve
  - Somewhat approve
  - Somewhat disapprove
  - Strongly disapprove
- How likely would you be to vote for the governor in the next election?
  - Very likely
  - Somewhat likely
  - Somewhat unlikely
  - Very unlikely
- How would you assign blame for the budget shortfall mentioned above? The total cannot exceed 100.
  - President
  - US Congress
  - State governor
  - State legislature
  - Other
- Thinking about the governor mentioned above, how well do you think the following traits describe him? intelligent; provides strong leadership; honest; competent; trustworthy.
  - Not well at all (1)
  - Slightly well (2)
  - Moderately well (3)
  - Very well (4)
  - Extremely well (5)

Heat Wave Study

Study Description

We fielded our heat wave study on Amazon's Mechanical Turk (MTurk) on October 18, 2017. We recruited 1006 respondents, 879 of which passed our attention check and provided responses to at least one of our key outcome measures. Vignette wording is displayed in Table 1, and post-treatment question wording is provided below.

Question Wording

- Do you approve or disapprove of the mayor's handling of the heat wave?
  - Strongly approve
  - Somewhat approve
  - Somewhat disapprove
  - Strongly disapprove
- How likely would you be to vote for the mayor in the next election?
  - Very likely
  - Somewhat likely
  - Somewhat unlikely
  - Very unlikely
- How would you assign blame for the heat wave mentioned above? The total cannot exceed 100.
  - President
  - US Congress
  - Federal Emergency Management Agency
  - State governor
  - Mayor
  - City council
  - City's emergency management agency
  - Other
- Thinking about the mayor mentioned above, how well do you think the following traits describe him? intelligent; provides strong leadership; honest; competent; trustworthy.
  - Not well at all (1)
  - Slightly well (2)
  - Moderately well (3)
  - Very well (4)
  - Extremely well (5)

Bridge Collapse Study (Factorial)

Study Description

We fielded our bridge collapse factorial study on Amazon's Mechanical Turk (MTurk) from October 20, 2017 to October 21, 2017. We recruited 1060 respondents, 871 of which passed our attention check and provided responses to at least one of our key outcome measures. Vignette wording and post-treatment question wording are provided below.

Vignette Wording

All respondents are presented with the following vignette, which contains three independently randomized factors with the levels specified below:

Earlier this year, a highway bridge running through a large American city collapsed during rush hour. The collapse sent [crisis severity]. A report prepared by federal investigators revealed that state officials identified the bridge as being in poor condition several years ago but had not taken any action to fix it. Critics have argued that the state's [governor's party affiliation] governor is to blame for the bridge collapse.

[Governor's response]

Attributes and *Levels*:

- **Crisis Severity**
  - *Control/Low*: many cars into the water below and caused several injuries
  - *Moderate*: many cars into the water below and caused 5 deaths and several more injuries
  - *High*: many cars into the water below and caused 20 deaths and several more injuries
- **Governor's Party Affiliation**
  - *Control*: (blank)
  - *Democratic*: Democratic
  - *Republican*: Republican
- **Governor's Response**
  - *Control*: In a statement, the governor pledged to review the condition of the state's bridges and to make all necessary repairs to prevent future bridge collapses.
  - *Blame claim*: In a statement, the governor said that he is ultimately responsible for the safety of the state's roadways and accepted blame for his role in the bridge collapse. The governor pledged to review the condition of the state's bridges and to make all necessary repairs to prevent future bridge collapses.
  - *Blame deflect*: In a statement, the governor denied responsibility and blamed the state's department of transportation for its role in the bridge collapse. The governor pledged to review the condition of the state's bridges and to make all necessary repairs to prevent future bridge collapses.

Question Wording

- Do you approve or disapprove of the governor's handling of the bridge collapse?
  - strongly approve
  - somewhat approve
  - somewhat disapprove
  - strongly disapprove
- How likely would you be to vote for the governor in the next election?
  - very likely
  - somewhat likely
  - somewhat unlikely
  - very unlikely
- How would you assign blame for the bridge collapse mentioned above? The total cannot exceed 100.
  - President
  - US Congress
  - US Department of Transportation
  - State governor
  - State legislature
  - State department of transportation
  - Other
- Thinking about the governor mentioned above, how well do you think the following traits describe him? intelligent; provides strong leadership; honest; competent; trustworthy.
  - Not well at all (1)
  - Slightly well (2)
  - Moderately well (3)
  - Very well (4)
  - Extremely well (5)

Budget Shortfall Study (Factorial)

Study Description

We fielded our budget shortfall factorial study on Amazon's Mechanical Turk (MTurk) from October 20, 2017 to October 21, 2017. We recruited 1060 respondents, 872 of which passed our attention check and provided responses to at least one of our key outcome measures. Vignette wording and post-treatment question wording are provided below.

Vignette Wording

All respondents are presented with the following vignette, which contains three independently randomized factors with the levels specified below:

Earlier this year, it was announced that a U.S. state faces a [crisis severity] budget deficit for the coming fiscal year. A non-partisan report finds that the deficit is a result of changes made last year to the state's tax policies. The report argues that these policies have generated less revenue than expected. Critics argue that the state's [governor's party affiliation] governor is to blame for the budget deficit.

[Governor's response]

Attributes and *Levels*:

- **Crisis Severity**
  - *Control/Low*: $5 million
  - *Moderate*: $50 million
  - *High*: $ 500 million
- **Governor's Party Affiliation**
  - *Control*: (blank)
  - *Democratic*: Democratic
  - *Republican*: Republican
- **Governor's Response**
  - *Control*: In a statement, the governor said that he is committed to working to balance the state's budget.
  - *Blame claim*: In a statement, the governor said that he is ultimately responsible for the fiscal health of the state and has accepted blame for his role in crafting the tax policies which caused the budget deficit. The governor said that he is committed to working to balance the state's budget.
  - *Blame deflect*: In a statement, the governor has denied responsibility and blamed the state legislature for their role in crafting the tax policies which caused the budget deficit. The governor said that he is committed to working to balance the state's budget.

Question Wording

- Do you approve or disapprove of the governor's handling of the budget shortfall?
  - strongly approve
  - somewhat approve
  - somewhat disapprove
  - strongly disapprove
- How likely would you be to vote for the governor in the next election?
  - very likely
  - somewhat likely
  - somewhat unlikely
  - very unlikely
- How would you assign blame for the budget shortfall mentioned above? The total cannot exceed 100.
  - President
  - US Congress
  - State governor
  - State legislature
  - Other
- Thinking about the governor mentioned above, how well do you think the following traits describe him? intelligent; provides strong leadership; honest; competent; trustworthy.
  - Not well at all (1)
  - Slightly well (2)
  - Moderately well (3)
  - Very well (4)
  - Extremely well (5)

Heat Wave Study (Factorial)

Study Description

We fielded our heat wave factorial study on Amazon's Mechanical Turk (MTurk) from October 20, 2017 to October 21, 2017. We recruited 1060 respondents, 872 of which passed our attention check and provided responses to at least one of our key outcome measures. Vignette wording and post-treatment question wording are provided below.

Vignette Wording

All respondents are presented with the following vignette, which contains three independently randomized factors with the levels specified below:

This summer, a major American city experienced a severe heat wave, with temperatures exceeding 100°F for five consecutive days. This excessive heat caused many residents to experience heat related illness and led to [crisis severity]. A recent report concluded that the city's handling of the heat wave was inadequate, and that the city should have opened cooling centers and conducted wellness checks on the elderly. Critics argue that the city's [mayor's party affiliation] mayor is to blame for the inadequate handling of the heat wave.
[Mayor's response]

Attributes and *Levels*:

- **Crisis Severity**
  - *Control/Low*: several hospitalizations
  - *Moderate*: 1 death and several hospitalizations
  - *High*: 20 deaths and several hospitalizations
- **Mayor's Party Affiliation**
  - *Control*: (blank)
  - *Democratic*: Democratic
  - *Republican*: Republican
- **Mayor's Response**
  - *Control*: In a statement, the mayor pledged to review the city's response plan for future heat waves.
  - *Blame claim*: In a statement, the mayor said that he is ultimately responsible for the safety of the city's residents and accepted blame for his role in the casualties caused by the heat wave. The mayor pledged to review the city's response plan for future heat waves.
  - *Blame deflect*: In a statement, the mayor denied responsibility and blamed the city's emergency management agency for its role in the casualties caused by the heat wave. The mayor pledged to review the city's response plan for future heat waves.

Question Wording

- Do you approve or disapprove of the mayor's handling of the heat wave?
  - strongly approve
  - somewhat approve
  - somewhat disapprove
  - strongly disapprove
- How likely would you be to vote for the mayor in the next election?
  - very likely
  - somewhat likely
  - somewhat unlikely
  - very unlikely
- How would you assign blame for the heat wave mentioned above? The total cannot exceed 100.
  - President
  - US Congress
  - Federal Emergency Management Agency
  - State governor
  - Mayor
  - City council
  - City's emergency management agency
  - Other
- Thinking about the mayor mentioned above, how well do you think the following traits describe him? intelligent; provides strong leadership; honest; competent; trustworthy.
  - Not well at all (1)
  - Slightly well (2)
  - Moderately well (3)
  - Very well (4)
  - Extremely well (5)

Flint Water Crisis Study

Study Description

We fielded our Flint water crisis study on Amazon's Mechanical Turk (MTurk) on March 30, 2016. We recruited 1010 respondents, 851 of which passed our attention check and provided responses to at least one of our key outcome measures. Vignette wording and post-treatment question wording are provided below.

Vignette Wording

All respondents are presented with one of the following vignettes:

Control: One year after the city of Flint, Michigan switched the source of its drinking water, investigators discovered that the city's water had become contaminated with unsafe levels of lead. Many argue that Michigan Governor Rick Snyder is ultimately responsible for the lead contamination crisis because this disaster occurred on his watch.

Blame claim: One year after the city of Flint, Michigan switched the source of its drinking water, investigators discovered that the city's water had become contaminated with unsafe levels of lead. Many argue that Michigan Governor Rick Snyder is ultimately responsible for the lead contamination crisis because this disaster occurred on his watch.

In a recent speech, Governor Snyder stated that "the buck stops here with me," and took "full responsibility to fix the problem."

Blame Appointee: One year after the city of Flint, Michigan switched the source of its drinking water, investigators discovered that the city's water had become contaminated with unsafe levels of lead. Many argue that Michigan Governor Rick Snyder is ultimately responsible for the lead contamination crisis because this disaster occurred on his watch.

Others point to a task force that found that Dan Wyant, the director of the Michigan Department of Environmental Quality (MDEQ), held "primary responsibility" for the crisis. Governor Snyder appointed Wyant as director of MDEQ in 2011.

Blame Bureaucrat: One year after the city of Flint, Michigan switched the source of its drinking water, investigators discovered that the city's water had become contaminated with unsafe levels of lead. Many argue that Michigan Governor Rick Snyder is ultimately responsible for the lead contamination crisis because this disaster occurred on his watch.

Others point to a task force that found that Dan Wyant, the director of the Michigan Department of Environmental Quality (MDEQ), held "primary responsibility" for the crisis. Prior to leading the MDEQ, Wyant had over 20 years of experience in state government, including 9 years as the director of the state's Department of Agriculture under both Republican and Democratic governors.

Question Wording

- How would you rate the job that Governor Snyder has done handling the Flint water crisis?
  - Very positive
  - Somewhat positive
  - Somewhat negative
  - Very negative
- Based on how you think Governor Snyder has handled the Flint water crises, do you think he should resign from or remain in office?
  - Resign from office
  - Remain in office
  - Not sure

Supplemental Analyses

Governmental Crises Studies

In this section of the Supplemental Information, we present the data and models used to create the figures in the main paper for our flood, bridge collapse, budget shortfall, and heat wave studies, which we refer to collectively here as our "governmental crises studies," as well as supplemental analyses for each of our experiments to demonstrate the robustness of our results to alternative specifications. Here, we provide an overview of our data and modeling strategies and discussion of how we coded our our outcome measures.

We present the distributions of our approval and vote choice outcome measures, both of which are four-point ordinal scales, in Figure SI.1. All models in the main paper used to estimate overall treatment effects are linear regression models which use dichotomized versions of our outcome variables (i.e., 1 if the respondent approves of the executive's handling of the governmental crisis or is likely to vote for the executive in the next election, and 0 otherwise). To account for the dichotomous nature of our outcome variables, we refit our models using logistic regressions. We also utilize the original ordinal forms of our outcome variables, some of which are ordered and others of which are unordered, to refit out models using ordinal logistic regression and multinomial logistic regression, respectively. Across each of these alternative model specifications, we consistently find that respondents evaluate elected executives more positively when the executives claim blame, as compared to when they blame deflect or offer a perfunctory response (as in the control condition).

One key difference between our flood study and our bridge collapse, budget shortfall, and heat wave studies is the form of our outcome measures. While our flood study offered respondents unordered five-point scales which also included a "don't know" option, our other studies offered respondents ordered four-point scales. For example, when asked to indicate their approval for the executive's handling of the crisis, respondents in our bridge collapse, budget shortfall, and heat wave studies were able to select among strongly approve, somewhat approve, somewhat disapprove, or strongly disapprove, while respondents in our flood study were also able to select "don't know." In the main paper, we make our analyses consistent across our studies by coding the outcome measures in all of our studies as 1 if they evaluate the executive favorably (e.g., 1 if strongly or somewhat approve of the executive's handling of the crisis), and 0 otherwise. In this coding scheme, respondents in the flood study offering "don't know" responses are coded as "not evaluating the executive favorably." As several scholars have indicated, "don't know" responses are qualitatively different from other response choices, such as positive or negative evaluations of an elected official, such that collapsing "don't know" responses with negative evaluations may lead to bias in our observed treatment effects (e.g., Mondak 2001).[38] As a result, we reestimate our models for our flood study using multinomial logistic regression, which allows us to estimate the effect of treatment on respondents' propensity to offer positive evaluations, negative evaluations, or "don't know" responses. The results from these models are substantively similar to those presented in the main paper, suggesting that our observed treatment effects are not contingent on how we account for "don't know" responses.

Finally, the three studies we fielded on mTurk (bridge collapse, budget shortfall, and heat wave) were completed by a single sample of respondents in the same survey, with the order of the studies and the presentational strategies used by the featured executives randomized across respondents. While including multiple experiments in the same survey is logistically efficient, respondents' answers in experimental modules later in the survey can sometimes be influenced by the experimental modules they completed earlier (i.e. ordering effects) (Gaines, Kuklinski, and Quirk 2007). For instance, a treatment a respondent received in the first study they completed might affect how they respond to a treatment in a later study. Again, by completing the same type of study multiple times, respondents might intuit the purpose of the survey over the course of multiple studies and offer responses in later studies that satisfy the researchers' aims. We investigate the potential for ordering effects by estimating our treatment effects for the first, second, and third studies that respondents completed, pooling across the substantive contexts of those studies. These results, presented in Table SI.11 SI.12, suggest that our results are not an artifact of ordering effects. First, the treatment effects among respondents in their first study are substantively similar to those presented in the main paper; thus, before having completed any other studies, respondents express more positive (negative) evaluations for executives who claim (deflect) blame. Second, the treatment effects are substantively similar across studies given their temporal order, suggesting that respondents' treatment assignments in previous studies did not affect the treatment effects observed in subsequent studies.

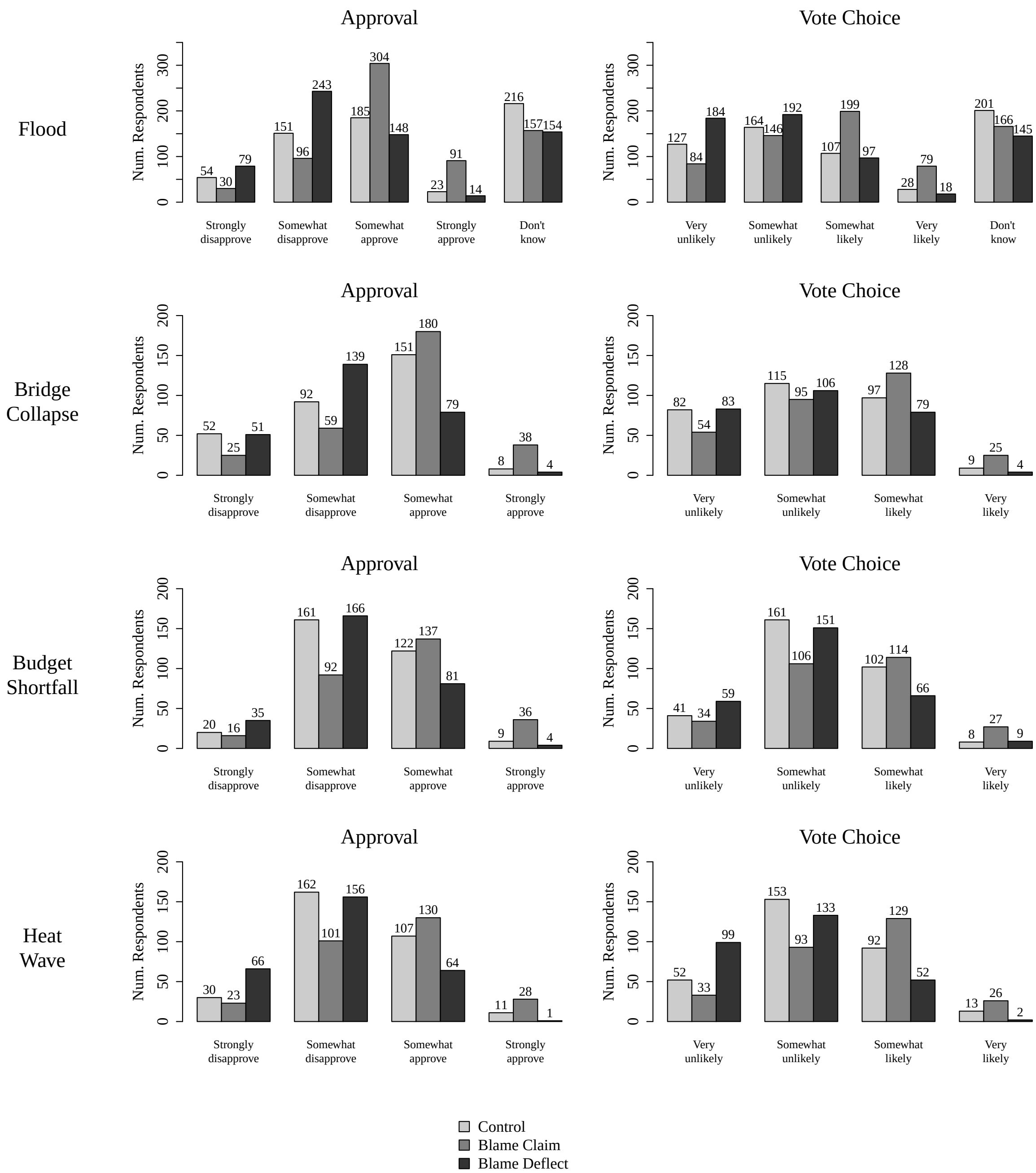

Figure SI.1: **Distributions of Outcome Measures for Studies of Four Governmental Crises.** Each plot in this figure presents the number of respondents in each experiment (indicated by the row labels) offering each of the unique response options for each outcome measure (indicated by the column headings). The legend at the bottom indicates which treatment conditions correspond to the bars of which color.

Table SI.1: Governmental Crises Models—Handling (OLS with Binary Outcome)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	0.29*	0.52*	0.42*	0.38*
	(0.02)	(0.03)	(0.03)	(0.03)
Blame Claim	0.23*	0.20*	0.20*	0.18*
	(0.03)	(0.04)	(0.04)	(0.04)
Blame Deflect	−0.06*	−0.22*	−0.12*	−0.15*
	(0.03)	(0.04)	(0.04)	(0.04)
R^2	0.07	0.11	0.07	0.08
Num. obs.	1945	878	879	879

*$p < 0.05$. This table presents the the linear regression models we used to construct the plots for the results of our flood, bridge collapse, budget shortfall, and heat wave studies displayed in the main analysis of the paper. Our outcome variable, approval of the executive's handling of the governmental crisis, is coded as a dichotomous variable (1 if strongly approve or approve, 0 otherwise). The control condition is the baseline condition. Flood model includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.2: Governmental Crises Models—Vote (OLS with Binary Outcome)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	0.23*	0.35*	0.35*	0.34*
	(0.02)	(0.03)	(0.03)	(0.03)
Blame Claim	0.15*	0.16*	0.15*	0.21*
	(0.02)	(0.04)	(0.04)	(0.04)
Blame Deflect	−0.04	−0.04	−0.09*	−0.15*
	(0.02)	(0.04)	(0.04)	(0.04)
R^2	0.03	0.03	0.04	0.09
Num. obs.	1937	877	878	877

*$p < 0.05$. This table presents the the linear regression models we used to construct the plots for the results of our flood, bridge collapse, budget shortfall, and heat wave studies displayed in the main analysis of the paper. Our outcome variable, likelihood of voting for the executive in the next election, is coded as a dichotomous variable (1 if very likely or likely, 0 otherwise). The control condition is the baseline condition. Flood model includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.3: Governmental Crises Models—Handling (OLS with Ordinal Outcome)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	2.39*	2.38*	2.38*	2.32*
	(0.04)	(0.04)	(0.04)	(0.04)
Blame Claim	0.42*	0.39*	0.30*	0.26*
	(0.05)	(0.06)	(0.06)	(0.06)
Blame Deflect	−0.20*	−0.25*	−0.20*	−0.32*
	(0.05)	(0.06)	(0.06)	(0.06)
R^2	0.10	0.10	0.08	0.10
Num. obs.	1418	878	879	879

*$p < 0.05$. This table presents the the linear regression models we used to construct the plots for the results of our flood, bridge collapse, budget shortfall, and heat wave studies displayed in the main analysis of the paper. Our outcome variable, approval of the executive's handling of the governmental crisis, is coded as a four-point an ordinal variable. Because "don't know" outcome responses do not fit into an ordinal framework, these responses in the flood study are recoded as NAs for these models only. The control condition is the baseline condition. Flood model includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.4: Governmental Crises Models—Vote (OLS with Ordinal Outcome)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	2.11*	2.11*	2.25*	2.21*
	(0.04)	(0.05)	(0.04)	(0.04)
Blame Claim	0.37*	0.30*	0.23*	0.31*
	(0.06)	(0.07)	(0.06)	(0.06)
Blame Deflect	−0.18*	−0.09	−0.16*	−0.36*
	(0.06)	(0.07)	(0.06)	(0.06)
R^2	0.06	0.04	0.04	0.11
Num. obs.	1425	877	878	877

*$p < 0.05$. This table presents the the linear regression models we used to construct the plots for the results of our flood, bridge collapse, budget shortfall, and heat wave studies displayed in the main analysis of the paper. Our outcome variable, respondents' likelihood of voting for the executive in the next election, is coded as a four-point an ordinal variable. Because "don't know" outcome responses do not fit into an ordinal framework, these responses in the flood study are recoded as NAs for these models only. The control condition is the baseline condition. Flood model includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.5: Governmental Crises Models—Handling (Logistic Regression)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	-0.88^{*}	0.10	-0.32^{*}	-0.49^{*}
	(0.09)	(0.12)	(0.11)	(0.12)
Blame Claim	0.99^{*}	0.85^{*}	0.79^{*}	0.73^{*}
	(0.12)	(0.17)	(0.17)	(0.17)
Blame Deflect	-0.30^{*}	-0.93^{*}	-0.54^{*}	-0.74^{*}
	(0.13)	(0.17)	(0.17)	(0.18)
Log Likelihood	-1120.19	-555.88	-573.45	-552.91
Num. obs.	1945	878	879	879

$^{*}p < 0.05$. This table presents the the logistic regression models that are analogous to the linear regression models we used to estimate the results presented in the main analysis of the paper. Our outcome variable, approval of the executive's handling of the governmental crisis, is coded as a dichotomous variable (1 if strongly approve or approve, 0 otherwise). The control condition is the baseline condition. Flood model includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.6: Governmental Crises Models—Vote (Logistic Regression)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	-1.18^{*}	-0.62^{*}	-0.61^{*}	-0.67^{*}
	(0.09)	(0.12)	(0.12)	(0.12)
Blame Claim	0.69^{*}	0.65^{*}	0.61^{*}	0.88^{*}
	(0.12)	(0.17)	(0.17)	(0.17)
Blame Deflect	-0.24	-0.20	-0.42^{*}	-0.79^{*}
	(0.14)	(0.18)	(0.18)	(0.19)
Log Likelihood	-1052.71	-572.77	-561.52	-530.30
Num. obs.	1937	877	878	877

$^{*}p < 0.05$. This table presents the the logistic regression models that are analogous to the linear regression models we used to estimate the results presented in the main analysis of the paper. Our outcome variable, likelihood of voting for the executive in the next election, is coded as a dichotomous variable (1 if very likely or likely, 0 otherwise). The control condition is the baseline condition. Flood model includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.7: Governmental Crises Models—Handling (Ordinal Logistic Regression)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Blame Claim	1.02*	1.01*	0.84*	0.69*
	(0.13)	(0.16)	(0.16)	(0.16)
Blame Deflect	−0.50*	−0.63*	−0.54*	−0.82*
	(0.13)	(0.15)	(0.16)	(0.16)
Strongly disapprove—Disapprove	−1.93*	−1.79*	−2.47*	−2.04*
	(0.12)	(0.13)	(0.15)	(0.14)
Disapprove—Approve	0.16	0.01	0.32*	0.44*
	(0.10)	(0.11)	(0.11)	(0.11)
Approve—Strongly approve	2.64*	3.15*	3.05*	3.15*
	(0.13)	(0.18)	(0.18)	(0.19)
Log Likelihood	-1560.81	-971.70	-918.00	-951.91
Num. obs.	1418	878	879	879

*$p < 0.05$. This table presents the the ordinal logistic regression models that are analogous to the linear regression models we used to estimate the results presented in the main analysis of the paper. Our outcome variable, approval of the executive's handling of the governmental crisis, is coded as a four-point an ordinal variable. Because "don't know" outcome responses do not fit into an ordinal framework, these responses in the flood study are recoded as NAs for these models only. The control condition is the baseline condition. Flood model includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.8: Governmental Crises Models—Vote (Ordinal Logistic Regression)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Blame Claim	0.73*	0.65*	0.56*	0.78*
	(0.12)	(0.15)	(0.16)	(0.16)
Blame Deflect	−0.37*	−0.19	−0.42*	−0.86*
	(0.12)	(0.15)	(0.15)	(0.16)
Very unlikely—Somewhat unlikely	−0.80*	−0.97*	−1.73*	−1.49*
	(0.09)	(0.11)	(0.13)	(0.12)
Somewhat unlikely—Somewhat likely	0.65*	0.62*	0.58*	0.60*
	(0.09)	(0.11)	(0.11)	(0.11)
Somewhat likely—Very likely	2.51*	3.32*	3.05*	3.17*
	(0.12)	(0.19)	(0.18)	(0.19)
Log Likelihood	-1770.01	-1051.21	-995.47	-998.39
Num. obs.	1425	877	878	877

*$p < 0.05$. This table presents the the ordinal logistic regression models that are analogous to the linear regression models we used to estimate the results presented in the main analysis of the paper. Our outcome variable, likelihood of voting for the executive in the next election, is coded as a four-point an ordinal variable. Because "don't know" outcome responses do not fit into an ordinal framework, these responses in the flood study are recoded as NAs for these models only. The control condition is the baseline condition. Flood model includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.9: Flood Study Models—Handling (Multinomial Logistic Regression)

	Strongly disagree	Disagree	Agree	Strongly agree
Intercept	-1.49^{*}	-0.43^{*}	-0.38^{*}	-2.33^{*}
	(0.15)	(0.10)	(0.10)	(0.22)
Blame Claim	-0.18	0.06	0.85^{*}	1.65^{*}
	(0.24)	(0.16)	(0.14)	(0.26)
Blame Deflect	0.72^{*}	0.73^{*}	0.10	0.15
	(0.21)	(0.15)	(0.16)	(0.33)
Log Likelihood	-2715.42	-2715.42	-2715.42	-2715.42
Num. obs.	1945	1945	1945	1945

$^{*}p < 0.05$. This table presents the a multinomial logistic regression model for approval of the mayor's handling of the flood. Our outcome variable is coded to account for responses of strongly disagree, disagree, agree, strongly agree, and doné know (which is the baseline response choice). The control condition is the baseline condition. Model includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.10: Flood Study Models—Vote (Multinomial Logistic Regression)

	Very unlikely	Unlikely	Likely	Very likely
Intercept	-0.43^{*}	-0.36^{*}	-0.57^{*}	-1.85^{*}
	(0.11)	(0.11)	(0.12)	(0.19)
Blame Claim	-0.35^{*}	0.11	0.60^{*}	0.79^{*}
	(0.17)	(0.15)	(0.15)	(0.24)
Blame Deflect	0.63^{*}	0.44^{*}	0.06	0.27
	(0.16)	(0.16)	(0.18)	(0.27)
Log Likelihood	-2915.60	-2915.60	-2915.60	-2915.60
Num. obs.	1937	1937	1937	1937

$^{*}p < 0.05$. This table presents the the multinomial logistic regression models for likelihood of voting for the mayor in the next election. Our outcome variable is coded to account for responses of very unlikely, unlikely, likely, very likely, and doné know (which is the baseline response choice). The control condition is the baseline condition. Models include survey weights; results remain substantively unchanged when weights are not included.

Table SI.11: MTurk Sample Ordering Effects—Handling (OLS with Binary Outcome)

	First Module	Second Module	Third Module
Intercept	0.41^*	0.46^*	0.45^*
	(0.03)	(0.03)	(0.03)
Blame Claim	0.21^*	0.19^*	0.18^*
	(0.04)	(0.04)	(0.04)
Blame Deflect	-0.18^*	-0.20^*	-0.13^*
	(0.04)	(0.04)	(0.04)
R^2	0.10	0.10	0.06
Num. obs.	879	879	878

$^*p < 0.05$. This table presents linear regression models we use to investigate whether the results from our studies which use our MTurk sample are artifacts of ordering effects. Our outcome variable, approval of the executive's handling of the governmental crisis, is coded as a dichotomous variable (1 if strongly approve or approve, 0 otherwise). The control condition is the baseline condition. To investigate ordering effects, we estimate the treatment effects for blame claiming and blame deflecting among respondents in each study (i.e., the first, second, and third studies they completed in the survey); if ordering effects are problematic, we would expect to see instability in the treatment effects given the temporal ordering of the studies. However, we see that the treatment effects for blame claiming and blame deflecting are substantively similar across temporal ordering of studies and in comparison to those presented in the main paper, which pool across each respondents' ordering for each study. This suggests that our results are not an artifact of ordering effects.

Table SI.12: MTurk Sample Ordering Effects—Vote (OLS with Binary Outcome)

	First Module	Second Module	Third Module
Intercept	0.30^*	0.37^*	0.38^*
	(0.03)	(0.03)	(0.03)
Blame Claim	0.17^*	0.18^*	0.16^*
	(0.04)	(0.04)	(0.04)
Blame Deflect	-0.07	-0.14^*	-0.08^*
	(0.04)	(0.04)	(0.04)
R^2	0.05	0.07	0.04
Num. obs.	877	879	876

$^*p < 0.05$. This table presents linear regression models we use to investigate whether the results from our studies which use our MTurk sample are artifacts of ordering effects. Our outcome variable, likelihood of voting for the executive in the next election, is coded as a dichotomous variable (1 if very likely or likely, 0 otherwise). The control condition is the baseline condition. To investigate ordering effects, we estimate the treatment effects for blame claiming and blame deflecting among respondents in each study (i.e., the first, second, and third studies they completed in the survey); if ordering effects are problematic, we would expect to see instability in the treatment effects given the temporal ordering of the studies. However, we see that the treatment effects for blame claiming and blame deflecting are substantively similar across temporal ordering of studies and in comparison to those presented in the main paper, which pool across each respondents' ordering for each study. This suggests that our results are not an artifact of ordering effects.

Factorial Analyses

We use our factorial analyses to examine whether our blame claiming effects persist in more complex information environments. One way to assess this is to estimate the marginal effect for each unique level of each unique factor (except for the baseline factor-levels), and observe whether the blame claiming effect still manifests; if so, then we can conclude that introducing other salient information cues into the vignette, such as the crisis' severity and the partisan affiliation of the governor, does not obviate the effect of blame claiming. The first, third and fifth columns of Tables SI.13 and SI.14 conduct these analyses, and demonstrate that the blame claiming effect persists in the presence of other salient information cues.

Another way to assess the effect of blame claiming in more complex information environments is to examine whether the overall treatment effects we observe are conditioned by other aspects of the government crisis (i.e., whether the overall treatment effects are driven by conditional treatment effects in some crisis contexts or some respondent subgroups). Particularly, we investigate whether the effect of blame claiming is conditioned by the severity of the crisis and by the correspondence between the partisanship of the elected executive and the partisanship of the respondent. We can examine the first such conditional effect with an factor by factor interaction (the three levels of the response factor by the three levels of the severity factor), but the second such conditional effect requires additional data coding. In each of our factorial studies, we ask our respondents to identify their partisan affiliation in our pre-treatment question battery. We use these responses together with our indicators for the partisan affiliation of the executive presented to the respondent in the vignette to assess how their partisan affiliations correspond: partisan correspondence is coded as "copartisan" if the respondent and the executive share the same partisan affiliation (i.e., if they are both Democrats or Republicans); "noncopartisan" if the respondent and the executive have different partisan affiliations (i.e., if the executive is a Democrat and the respondent is a Republican, or vice versa); and "no match" if the elected executive is not assigned a partisan affiliation or the respondent identifies as an independent.

As examining these conditional effects in easier to do graphically than in a regression table, we present in Figures SI.2 through SI.5 the effects of blame claiming and blame deflecting under each unique factor-level for crisis severity and partisan correspondence as compared to the control condition. In each pairwise comparison, the crisis severity or partisan correspondence remains constant, while the presentational strategy used by the elected executive "changes" from the control response to the blame claiming or blame deflecting responses. As an example, in the upper left panel of Figure SI.2, we observe the effects of blame claiming and blame deflecting on respondents' approval of the executive's handling of the governmental crisis relative to the the control across each level of the severity factor. For each point estimate, we compare respondents' approval of the executive's handling of the governmental crisis when the control response is offered as compared to when the blame claiming or blame deflecting responses are offered while fixing the severity factor-level. Thus, the upper-most point in this plot compares respondents' approval when the elected executive claims blame in a low severity crisis to when the elected executive offers the control response in a low severity crisis.

As in the main paper, we use linear regressions with dichotomous forms of our outcome variables in each of our models. We alternatively refit each of our models using logistic and ordinal logistic regression models where appropriate; though not presented here, the results of our factorial analyses remain consistent across these alternative specifications.

Table SI.13: Factorial Experiments Models—Handling (OLS with Binary Outcome)

	Bridge Collapse	Bridge Collapse	Budget Shortfall	Budget Shortfall	Heat Wave	Heat Wave
Intercept	0.45***	0.45***	0.34***	0.34***	0.36***	0.31***
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
Blame Claim	0.26***	0.35***	0.28***	0.29***	0.18***	0.27**
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.08)
Blame Deflect	−0.13**	−0.19*	0.04	−0.01	−0.09*	−0.05
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.09)
Moderate Severity	−0.01	−0.02	0.00	−0.04	−0.04	−0.00
	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)	(0.07)
High Severity	−0.02	−0.11	−0.08*	−0.18**	0.01	0.04
	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)	(0.07)
Blame Claim x Moderate Severity		−0.01		0.06		−0.03
		(0.10)		(0.10)		(0.10)
Blame Claim x High Severity		0.05		0.18		−0.11
		(0.10)		(0.10)		(0.10)
Blame Deflect x Moderate Severity		0.02		0.13		−0.08
		(0.10)		(0.10)		(0.10)
Blame Deflect x High Severity		0.21*		0.13		0.04
		(0.09)		(0.10)		(0.10)
Copartisan	0.02	0.10	0.06	0.09	0.04	0.10
	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)	(0.07)
Noncopartisan	0.00	0.05	−0.02	0.07	−0.02	0.02
	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)	(0.07)
Blame Claim x Copartisan		−0.16		−0.09		−0.10
		(0.10)		(0.10)		(0.10)
Blame Claim x Noncopartisan		−0.23*		−0.19		−0.04
		(0.10)		(0.10)		(0.10)
Blame Deflect x Copartisan		−0.09		−0.01		−0.06
		(0.10)		(0.10)		(0.10)
Blame Deflect x Noncopartisan		0.05		−0.11		−0.04
		(0.09)		(0.10)		(0.10)
R^2	0.10	0.12	0.07	0.08	0.06	0.07
Num. obs.	844	844	845	845	845	845

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. This table presents linear regression analyses of our three factorial experiments. For each experimental context (bridge collapse, budget shortfall, and heat wave) we regress dichotomous indicators of respondents' approval of the executive's handling of the governmental crisis on dichotomous indicators for the levels of each factor (executive response, severity, and the correspondence between the party identifications of the respondent and the executive) presented to the respondents.

Table SI.14: Factorial Experiments Models—Vote (OLS with Binary Outcome)

	Bridge Collapse	Bridge Collapse	Budget Shortfall	Budget Shortfall	Heat Wave	Heat Wave
Intercept	0.34***	0.30***	0.29***	0.29***	0.32***	0.32***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.06)
Blame Claim	0.26***	0.40***	0.20***	0.25**	0.18***	0.21*
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.08)
Blame Deflect	−0.06	−0.03	0.03	−0.01	−0.09*	−0.11
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.08)
Moderate Severity	−0.01	0.00	−0.01	−0.03	−0.02	−0.04
	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)	(0.07)
High Severity	−0.03	−0.04	−0.03	−0.08	−0.01	0.05
	(0.04)	(0.06)	(0.04)	(0.07)	(0.04)	(0.07)
Blame Claim x Moderate Severity		−0.06		−0.02		0.06
		(0.10)		(0.09)		(0.09)
Blame Claim x High Severity		−0.02		0.18		−0.20*
		(0.10)		(0.10)		(0.10)
Blame Deflect x Moderate Severity		−0.03		0.14		−0.03
		(0.10)		(0.10)		(0.09)
Blame Deflect x High Severity		0.02		0.01		0.01
		(0.09)		(0.09)		(0.10)
Copartisan	0.08*	0.17**	0.13**	0.14*	0.12**	0.17*
	(0.04)	(0.06)	(0.04)	(0.07)	(0.04)	(0.07)
Noncopartisan	−0.10*	−0.03	−0.07	0.01	−0.05	−0.13
	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)	(0.06)
Blame Claim x Copartisan		−0.16		−0.08		−0.12
		(0.09)		(0.10)		(0.10)
Blame Claim x Noncopartisan		−0.27**		−0.22*		0.15
		(0.10)		(0.09)		(0.10)
Blame Deflect x Copartisan		−0.12		0.03		−0.03
		(0.09)		(0.10)		(0.09)
Blame Deflect x Noncopartisan		0.04		−0.04		0.12
		(0.09)		(0.09)		(0.09)
R^2	0.10	0.11	0.06	0.08	0.07	0.09
Num. obs.	841	841	845	845	844	844

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. This table presents linear regression analyses of our three factorial experiments. For each experimental context (bridge collapse, budget shortfall, and heat wave) we regress dichotomous indicators of respondents' likelihood of voting for the executive in the next election on dichotomous indicators for the levels of each factor (executive response, severity, and the correspondence between the party identifications of the respondent and the executive) presented to the respondents.

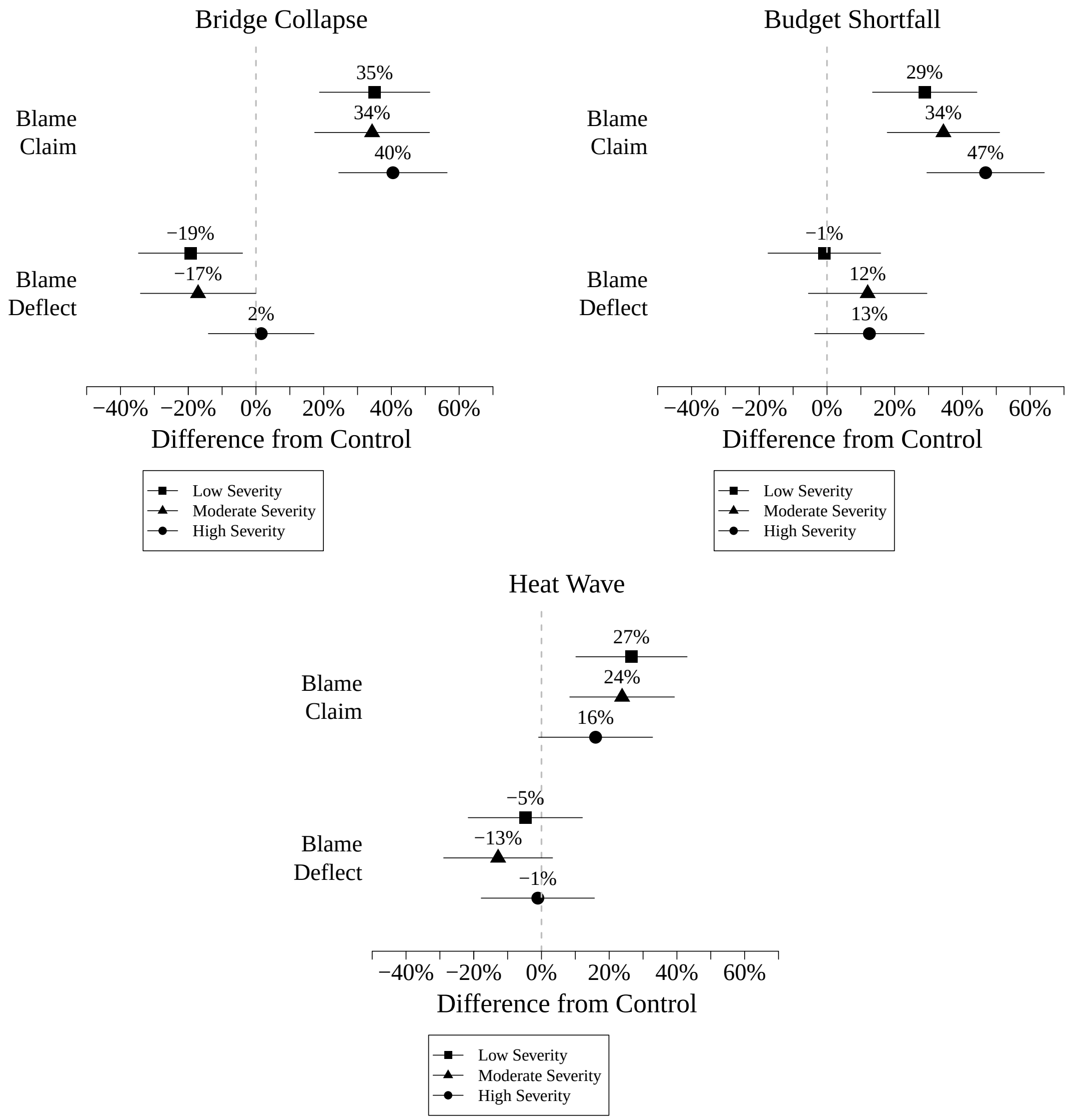

Figure SI.2: **Approval of Elected Executives' Handling of Crises (Response and Severity).** Linear regression coefficients for effects of blame claiming and blame deflecting on approval of the elected executive's handling of the crisis conditional on the severity of the crisis. Positive (negative) values along $x-$axis reflect more (less) favorable evaluations relative to the control condition. Each conditional AMCE compares the effect of blame claiming or blame deflecting relative to the control condition while fixing the level of the severity of the crisis; for example, in the bridge collapse plot (top left), when crisis severity is low, the treatment effects of blame claiming and blame deflecting relative to the control condition are 35% and -19%, respectively. We generally observe that the positive effect of blame claiming persists across levels of crisis severity, though blame deflecting does not induce any consistent treatment effects. Bars around point estimates represent 95 percent confidence intervals.

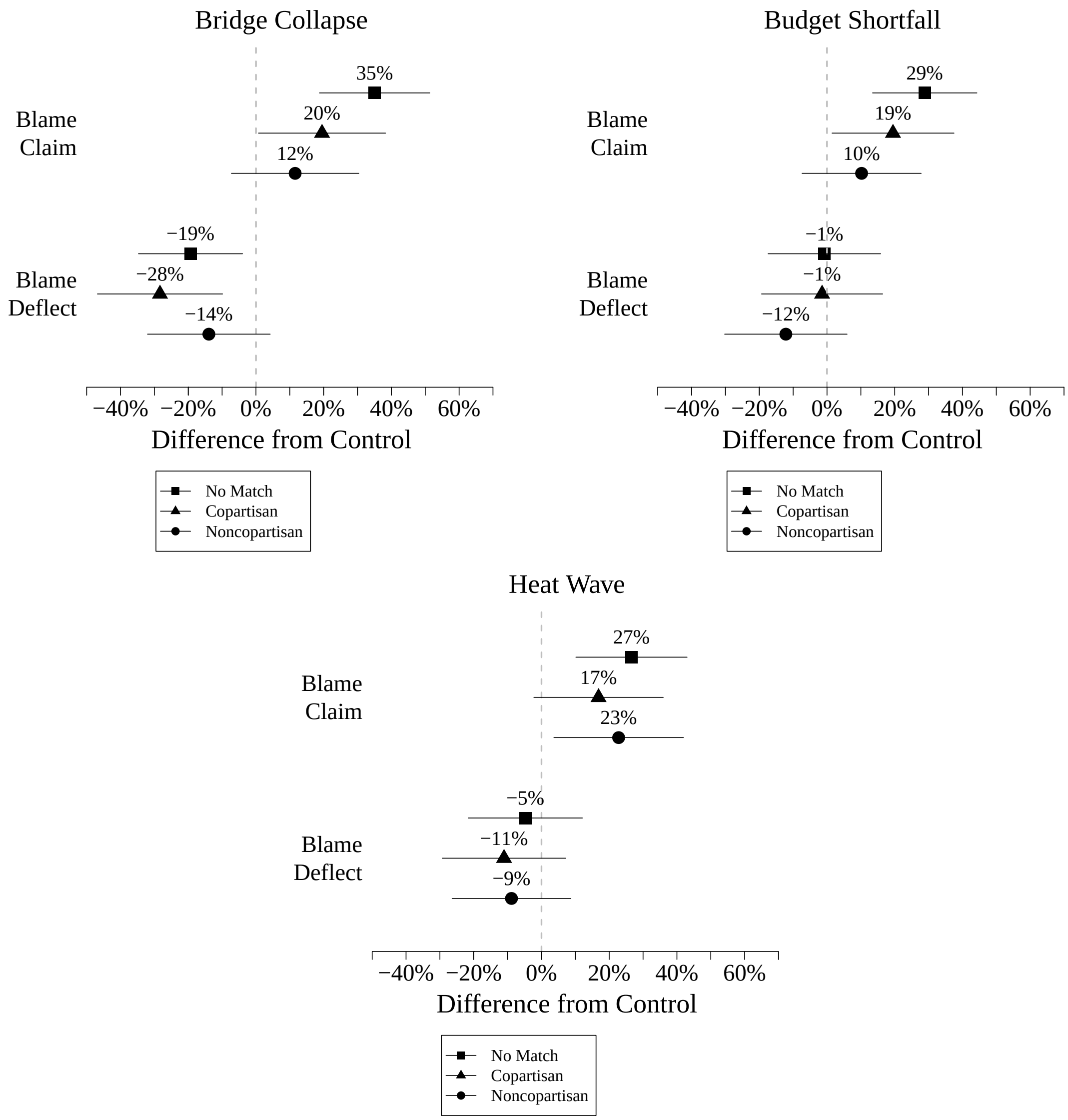

Figure SI.3: **Approval of Elected Executives' Handling of Crises (Response and Partisanship).** Linear regression coefficients for effects of blame claiming and blame deflecting on approval of the elected executive's handling of the crisis conditional on the correspondence between the partisanship of the respondent and the elected executive. Positive (negative) values along $x-$axis reflect more (less) favorable evaluations relative to the control condition. Each conditional AMCE compares the effect of blame claiming or blame deflecting relative to the control condition while fixing the correspondence between the partisanship of the respondent and the elected executive; for example, in the bridge collapse plot (top left), when both the respondent and the elected executive are of the same party, the treatment effects of blame claiming and blame deflecting relative to the control condition are 20% and -28%, respectively. We generally observe that the positive effect of blame claiming persists across levels of crisis severity, though blame deflecting does not induce any consistent treatment effects. Bars around point estimates represent 95 percent confidence intervals.

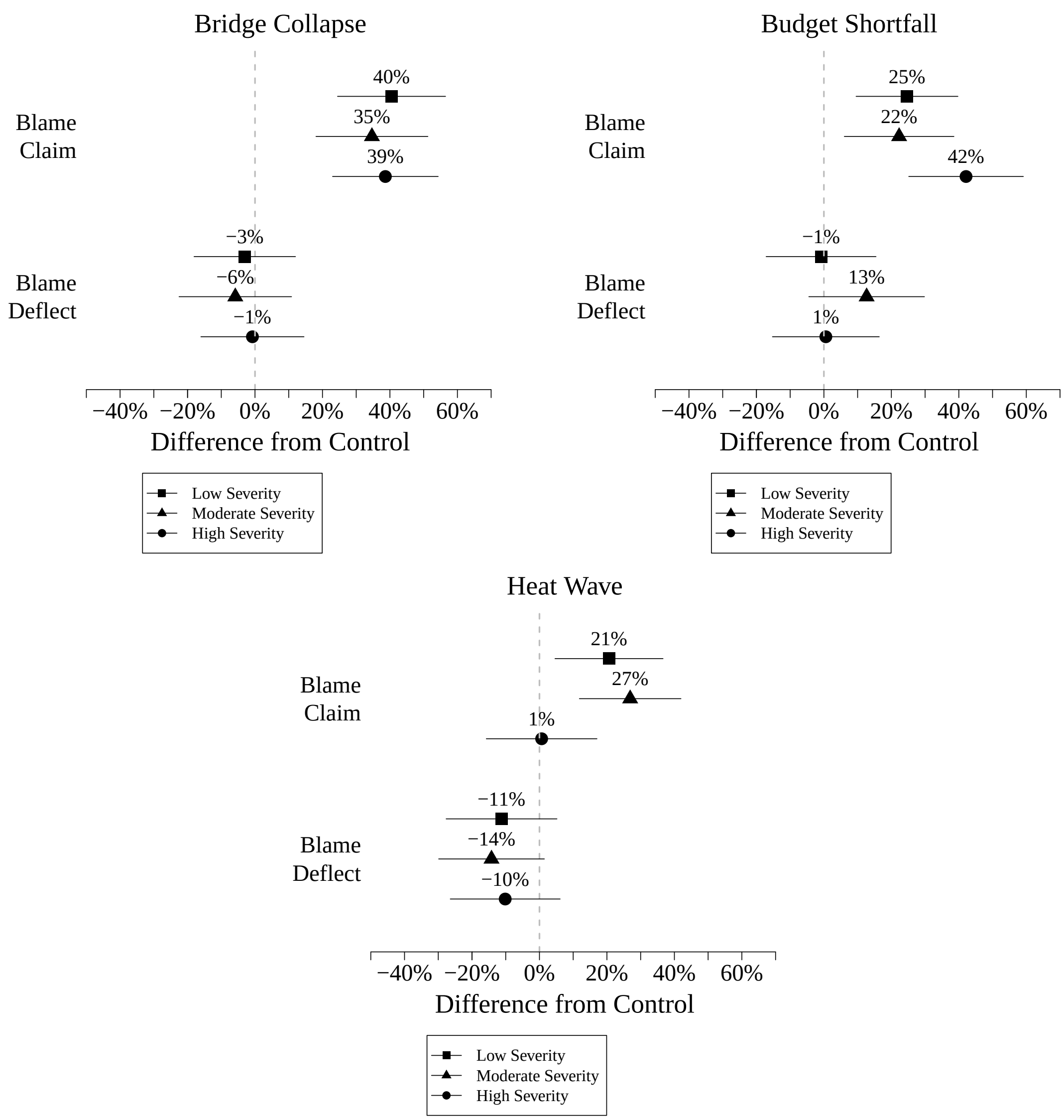

Figure SI.4: **Likelihood of Voting for Elected Executives (Response and Severity).** Linear regression coefficients for effects of blame claiming and blame deflecting on likelihood of voting for the elected executive in the next election conditional on the severity of the crisis. Positive (negative) values along $x-$axis reflect more (less) favorable evaluations relative to the control condition. Each conditional AMCE compares the effect of blame claiming or blame deflecting relative to the control condition while fixing the level of the severity of the crisis; for example, in the bridge collapse plot (top left), when crisis severity is low, the treatment effects of blame claiming and blame deflecting relative to the control condition are 40% and -3%, respectively. We generally observe that the positive effect of blame claiming persists across levels of crisis severity, though blame deflecting does not induce any consistent treatment effects. Bars around point estimates represent 95 percent confidence intervals.

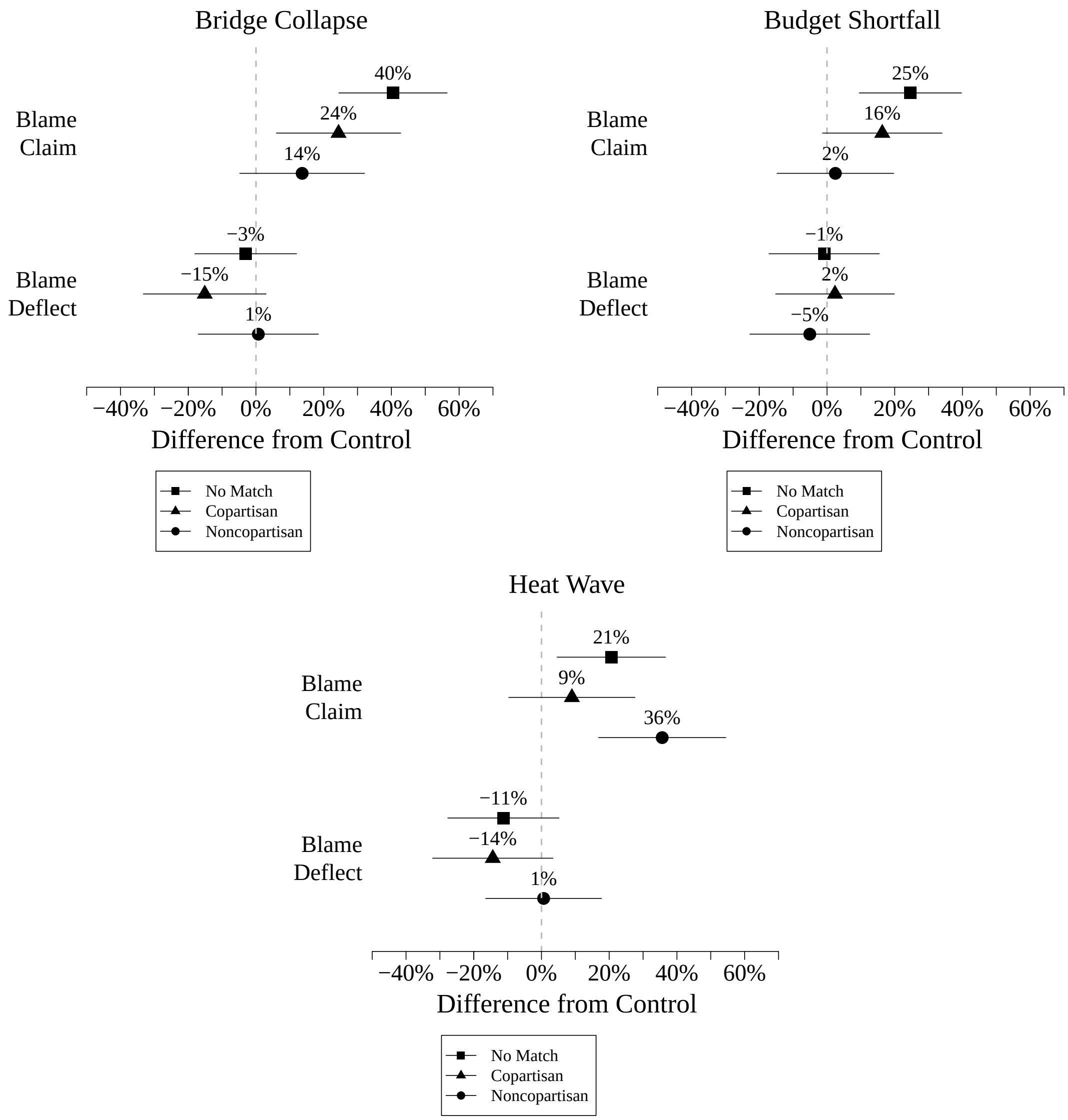

Figure SI.5: **Likelihood of Voting for Elected Executives (Response and Partisanship).** Linear regression coefficients for effects of blame claiming and blame deflecting on likelihood of voting for the elected executive in the next election conditional on the correspondence between the partisanship of the respondent and the elected executive. Positive (negative) values along $x-$axis reflect more (less) favorable evaluations relative to the control condition. Each conditional AMCE compares the effect of blame claiming or blame deflecting relative to the control condition while fixing the correspondence between the partisanship of the respondent and the elected executive; for example, in the bridge collapse plot (top left), when both the respondent and the elected executive are of the same party, the treatment effects of blame claiming and blame deflecting relative to the control condition are 24% and -15%, respectively. We generally observe that the positive effect of blame claiming persists across levels of crisis severity, though blame deflecting does not induce any consistent treatment effects. Bars around point estimates represent 95 percent confidence intervals.

Flint Study

In this section of the Supplemental Information, we present the data and models used to create the figures for our Flint water crisis experiment presented in the main paper, as well as supplemental analyses to demonstrate the robustness of our results to alternative model specifications. Here, we provide a general overview of our data and modeling strategies and a discussion of how we coded our outcome measures.

We present the distributions of our outcome measures in Figure SI.6. The models used to estimate the overall treatment effects are linear regression models which use dichotomized versions of our outcome variables (i.e., 1 if the respondent approves of Governor Snyder's handling of the Flint water crisis, and 0 otherwise). To account for the dichotomous nature of our outcome variables, we refit our models using logistic regressions. We also utilize the original ordinal forms of our outcome variables, one of which is ordered (approval) and the other of which is unordered (whether Governor Snyder should resign), to refit out models using ordinal logistic regression and multinomial logistic regression, respectively. Across each of these alternative model specifications, we consistently find that respondents evaluate Governor Snyder more positively when he claims blame for the Flint water crisis, as compared to when he deflects blame or offers no response (as in the control condition).

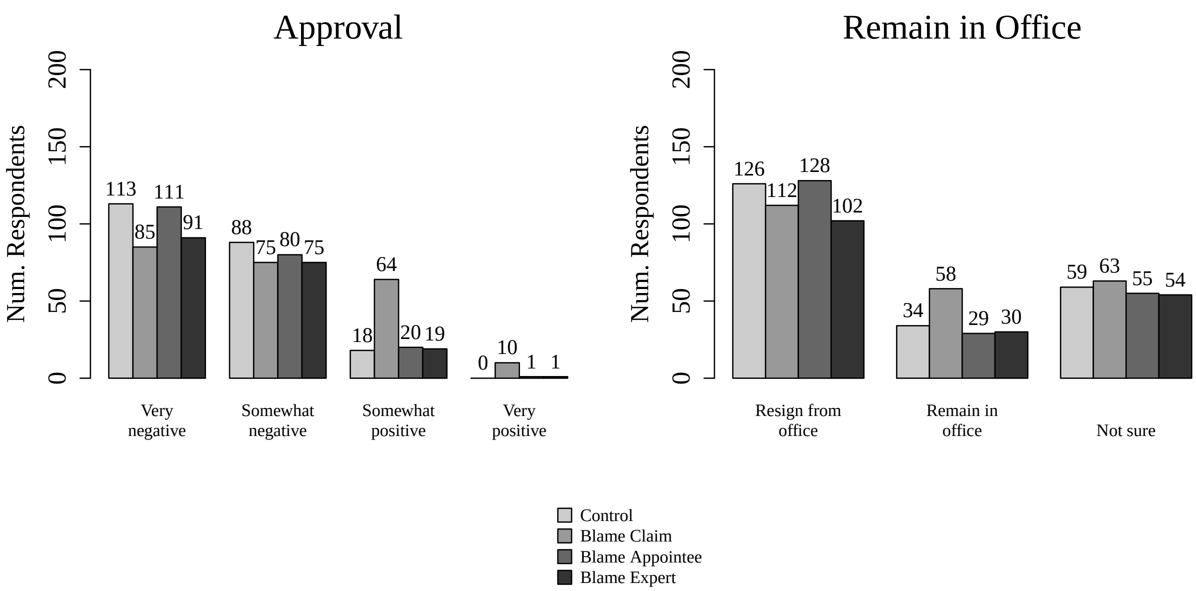

Figure SI.6: **Distributions of Outcome Measures for the Flint Study.** Each plot in this figure presents the number of respondents in our Flint study offering each of the unique response options for each outcome measure (indicated by the column headings). The legend at the bottom indicates which treatment conditions correspond to the bars of which color.

Table SI.15: Flint Study Models—Approval and Vote (OLS with Binary Outcome)

	Approval	Remain
Intercept	0.08*	0.16*
	(0.02)	(0.03)
Blame Claim	0.23*	0.09*
	(0.03)	(0.04)
Blame Appointee	0.02	−0.02
	(0.03)	(0.04)
Blame Expert	0.03	0.01
	(0.03)	(0.04)
R^2	0.07	0.01
Num. obs.	851	850

*$p < 0.05$. This table presents the linear regression models we used to construct the plots for the results of our Flint study displayed in the main analysis of the paper. Our outcome variables, approval of Governor Rick Snyder's handling of the Flint water crisis and whether the respondent thinks the governor should remain in office (as opposed to resign), are coded as dichotomous variables, and our covariates are dichotomous indicators of the respondents' treatment conditions. The control condition is the baseline condition.

Table SI.16: Flint Study Models—Approval and Vote (Logistic Regression)

	Approval	Remain
Intercept	-2.41^{*}	-1.69^{*}
	(0.25)	(0.19)
Blame Claim	1.64^{*}	0.59^{*}
	(0.28)	(0.24)
Blame Appointee	0.21	-0.15
	(0.34)	(0.27)
Blame Expert	0.30	0.05
	(0.34)	(0.27)
Log Likelihood	-340.19	-392.08
Num. obs.	851	850

$^{*}p < 0.05$. This table presents the logistic regression models that are analogous to the linear regression models we used to estimate the results presented in the main analysis of the paper. Our outcome variables, approval of Governor Rick Snyder's handling of the Flint water crisis and whether the respondent thinks the governor should remain in office (as opposed to resign), are coded as dichotomous variables, and our covariates are dichotomous indicators of the respondents' treatment conditions. The control condition is the baseline condition.

Table SI.17: Flint Study Models—Approval (OLS with Ordinal Outcome)

	Approval
Intercept	1.57^{*}
	(0.05)
Blame Claim	0.43^{*}
	(0.07)
Blame Appointee	0.01
	(0.07)
Blame Expert	0.06
	(0.07)
R^2	0.06
Num. obs.	851

$^{*}p < 0.05$. This table presents a linear regression model that uses a four-point scale of respondents' approval of Governor Rick Snyder as the outcome variable rather than the dichotomous measure of approval used in the main analysis presented in the paper. Our covariates are dichotomous indicators of the respondents' treatment conditions. The control condition is the baseline condition.

Table SI.18: Flint Study Models—Approval (Ordinal Logistic Regression)

	Approval
Blame Claim	0.96*
	(0.18)
Blame Appointee	0.01
	(0.18)
Blame Expert	0.13
	(0.19)
Very negative—Somewhat negative	0.14
	(0.13)
Somewhat negative—Somewhat positive	2.01*
	(0.15)
Somewhat positive—Very positive	4.63*
	(0.32)
Log Likelihood	-882.75
Num. obs.	851

*$p < 0.05$. This table presents an ordinal logistic regression model of approval for Governor Snyder's handling of the Flint water crisis that is analogous to the linear regression model we used to estimate the results presented in the main analysis of the paper. Our covariates are dichotomous indicators of the respondents' treatment conditions. The control condition is the baseline condition.

Table SI.19: Flint Study Models—Vote (Multinomial Logistic Regression)

	Remain in office	Not sure
Intercept	−1.31*	−0.76*
	(0.19)	(0.16)
Blame Claim	0.65*	0.18
	(0.25)	(0.22)
Blame Appointee	−0.17	−0.09
	(0.28)	(0.23)
Blame Expert	0.09	0.12
	(0.28)	(0.23)
Log Likelihood	-834.74	-834.74
Num. obs.	850	850

*$p < 0.05$. This table presents a multinomial logistic regression model of whether respondents think that Governor Snyder should remain in office (as opposed to resign) that is analogous to the linear regression model we used to estimate the results presented in the main analysis of the paper. Our outcome variable is trichotomous, with respondents indicating that the governor should resign from office (the baseline outcome), remain in office, or that they are not sure what the governor should do. Our covariates are dichotomous indicators of the respondents' treatment conditions. The control condition is the baseline condition.

Causal Mediation Analyses

In this section of the Supplemental Information, we describe and present models used to create the figures for the causal mediation analyses in the main paper. Here, we provide a general overview of our modeling strategy and discussion of how we coded our outcome and mediator measures.

All models in the main body of the paper used to conduct our causal mediation analyses are linear regression models. When regressing the mediator (either leadership valence or blameworthiness) on treatment, we use continuous measures of the mediator as our outcome variable. When regressing the outcome measures (either respondents' approval of the executive's handling of the governmental crisis or likelihood of voting for the executive in the next election) on treatment and the mediator, we use dichotomous measures of the outcome measures as our outcome variable. We alternatively conducted each of our causal mediation analyses using logistic and ordinal logistic regression models for the second model (i.e., regressing our outcome measures on treatment and the mediator); though not presented here, the results of our causal mediation analyses remain consistent across these alternative specifications.

We also present sensitivity analyses for the causal mediation analyses presented in the main paper which assess how leadership valence mediates the effect of blame claiming. These sensitivity analyses assess the irrefutable sequential ignorability assumption, which requires that treatment assignment is independent of potential outcomes and potential mediators, and the mediator value is independent of potential outcomes conditional on treatment assignment. The former component of the sequential ignorability assumption is identical to the ignorability assumption required to obtain an average treatment effect in a standard experiment, and the latter component further requires the absence of any pre-treatment or post-treatment variables that are correlated with both the mediator and the outcome of interest. In a standard experimental setting, this assumption is most commonly violated if any confounder exists for the relationship between the mediator and the outcome of interest. If no such confounder exists, then the correlation between the error terms in the mediator and outcome models, denoted as ρ, is 0. However, if the sequential ignorability assumption is violated, then ρ will be some non-zero value and our estimate of the ACME will be biased. However, because we cannot observe all potential confounders, either pre-treatment or post-treatment, this assumption is "irrefutable," as we cannot use the data we observe to substantiate the assumption (Imai, Keele, Tingley, and Yamamoto 2011, 770-771). In order to assess the robustness of the ACME, the sensitivity analysis proposed by Imai, Keele, Tingley, and Yamamoto (2011) varies the value of ρ from -1 to 1 to identify the values of ρ at which the ACME would equal 0 or change its sign, which allows us to make a qualitative assessment as to how robust the ACME is to violations of the sequential ignorability assumption. When using leadership valence to mediate the effect of blame claiming, our estimated ACMEs maintain statistical significance for $\rho \in [-1, 0.4]$ for both outcome measures across all four experiments, suggesting that, unless there is a confounder in the relationship between the mediator of leadership valence and the outcomes that induces a correlation in the error terms of $\rho \geq 0.4$, which is substantively large, then our ACMEs maintain their statisticaly significance.

Our mediators are both continuous variables, and are constructed as follows. First, our blameworthiness variable is the number of "blame points" (out of 100) each respondent assigns to the elected executive who is the subject of the vignette. Second, to construct our leadership valence variable, we use respondents' evaluations of five of the elected executives' character traits—intelligence, honesty, trustworthiness, strong leadership, and competence—to construct a single continuous scale. In our TAPS study, respondents are able to assess each of the character traits using a six-point unordered scale—extremely well, very well, moderately well, slightly well, not well at all, or not sure—, whereas respondents in our MTurk studies are provided with a five-point ordered scale which excludes the "not sure" option. To account for the different versions of our leadership valence outcome measures, we construct our scale slightly differently for our TAPS study and our MTurk studies. For our TAPS study, we transform each of the five character trait evaluations as dichotomous variables, where responses are coded as 1 if a respondent indicated that the character trait described the elected executive extremely well, very well, or moderately well, and 0 otherwise. Then, we used these dichotomous variables to create an additive scale of respondents' character traits, ranging from 0 to 5 (Cronbach's α =0.93). For our MTurk studies, we calculated the average of the respondents' trait evaluations across the five traits, such that the final scale ranged from 1 to 5 (Cronbach's α between 0.93 and 0.94 across each of the three MTurk studies).

Table SI.20: Causal Mediation Regressions (Leadership Valence on Treatment)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	1.44*	2.46*	2.46*	2.46*
	(0.08)	(0.06)	(0.05)	(0.05)
Blame Claim	1.15*	0.53*	0.59*	0.50*
	(0.12)	(0.08)	(0.08)	(0.08)
Blame Deflect	−0.19	−0.23*	−0.09	−0.34*
	(0.12)	(0.08)	(0.08)	(0.08)
R^2	0.08	0.10	0.09	0.11
Num. obs.	1916	875	875	871

$^*p < 0.05$. This table presents linear regression models of respondents' perceptions of the executives' leadership valence regressed on their treatment conditions, which were then used in the causal mediation analysis presented in the paper. The model in the first column uses an additive scale of respondents' perceptions of the executive's character traits (scaled from 0 to 5, where a value of 1 is added to the scale for every trait the respondent evaluates as describing the executive at least moderately well; Cronbach's α for this scale is 0.93) as the dependent variable, and dichotomous indicators of treatment assignment as the covariates (with the control condition as the baseline condition). The models in the other columns use an average of the respondents' perceptions of the executive's character traits (each trait is scaled from 1 to 5, as is the averaged scale; Cronbach's α exceeds 0.90 for each of these scales) as the dependent variable, and dichotomous indicators of treatment assignment as the covariates (with the control condition as the baseline condition). The model in the first column includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.21: Causal Mediation Regressions (Approval on Treatment and Leadership Valence)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	0.18^*	-0.17^*	-0.27^*	-0.29^*
	(0.02)	(0.04)	(0.04)	(0.04)
Blame Claim	0.14^*	0.05	0.03	0.05
	(0.02)	(0.03)	(0.03)	(0.03)
Blame Deflect	-0.05	-0.15^*	-0.10^*	-0.06
	(0.02)	(0.03)	(0.03)	(0.03)
Leadership Valence	0.08^*	0.28^*	0.28^*	0.27^*
	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.19	0.40	0.34	0.36
Num. obs.	1907	875	875	871

$^*p < 0.05$. This table presents linear regression models of respondents' approval of the executive's handling of the government crisis regressed on their treatment conditions, which were then used in the causal mediation analysis presented in the paper. All models use a dichomotous indicator of approval, coded as 1 if the respondent strongly approves or approves of the executive's handling of the governmental crisis, and coded as 0 otherwise. Covariates include dichotomous indicators of treatment assignment and scales of respondents' perceptions of the executive's leadership valence; see the notes in Table SI.20 for details on the coding of leadership valence. The model in the first column includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.22: Causal Mediation Regressions (Vote on Treatment and Leadership Valence)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	0.11^*	-0.42^*	-0.37^*	-0.36^*
	(0.02)	(0.04)	(0.04)	(0.04)
Blame Claim	0.03	-0.01	-0.02	0.07^*
	(0.02)	(0.03)	(0.03)	(0.03)
Blame Deflect	-0.03	0.03	-0.06	-0.06
	(0.02)	(0.03)	(0.03)	(0.03)
Character Valence	0.09^*	0.31^*	0.29^*	0.28^*
	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.22	0.40	0.35	0.41
Num. obs.	1899	874	874	869

$^*p < 0.05$. This table presents linear regression models of respondents' likelihood of voting for the executive in the next election regressed on their treatment conditions, which were then used in the causal mediation analysis presented in the paper. All models use a dichotomous indicator of likelihood of voting for the executive in the next election, coded as 1 if the respondent is very likely or somewhat likely to vote for the executive, and coded as 0 otherwise. Covariates include dichotomous indicators of treatment assignment and scales of respondents' perceptions of the executive's leadership valence; see the notes in Table SI.20 for details on the coding of leadership valence. The model in the first column includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.23: Causal Mediation Analysis—Leadership Valence and Approval

Context	Causal Quantity	Estimate	95% Confidence Interval
Flood	ACME	0.09	[0.06, 0.14]
(N=1907)	ADE	0.14	[0.05, 0.23]
	Total Effect	0.23	[0.15, 0.32]
	Prop. Mediated	0.41	[0.24, 0.70]
Bridge Collapse	ACME	0.15	[0.10, 0.20]
(N=875)	ADE	0.05	[-0.01, 0.12]
	Total Effect	0.20	[0.13, 0.28]
	Prop. Mediated	0.74	[0.52, 1.08]
Budget Shortfall	ACME	0.16	[0.12, 0.21]
(N=875)	ADE	0.03	[-0.03, 0.10]
	Total Effect	0.20	[0.13, 0.28]
	Prop. Mediated	0.83	[0.59, 1.26]
Heat Wave	ACME	0.14	[0.09, 0.18]
(N=871)	ADE	0.05	[-0.02, 0.12]
	Total Effect	0.18	[0.11, 0.26]
	Prop. Mediated	0.74	[0.50, 1.18]

$^{*}p < 0.05$. This table presents the causal mediation analyses results for the approval of the executive's handling of the governmental crisis outcome which are displayed in the main analysis of the paper. This causal mediation analysis uses the regression models in Tables SI.20 and SI.21. Only respondents for whom we have outcome measures for approval of the executive's handling of the governmental crisis and all five of the executive's character traits are included (i.e., respondents with missing outcomes are excluded). We conducted this analysis with 1000 simulations. 95% confidence intervals obtained through nonparametric bootstrap procedure (percentile method).

Table SI.24: Causal Mediation Analysis—Leadership Valence and Vote

Context	Causal Quantity	Estimate	95% Confidence Interval
Flood	ACME	0.11	[0.07, 0.15]
(N=1899)	ADE	0.03	[-0.05, 0.11]
	Total Effect	0.14	[0.06, 0.22]
	Prop. Mediated	0.78	[0.45, 1.68]
Bridge Collapse	ACME	0.17	[0.12, 0.21]
(N=874)	ADE	-0.01	[-0.07, 0.06]
	Total Effect	0.16	[0.08, 0.23]
	Prop. Mediated	1.06	[0.73, 1.79]
Budget Shortfall	ACME	0.17	[0.12, 0.22]
(N=874)	ADE	-0.02	[-0.09, 0.04]
	Total Effect	0.15	[0.07, 0.23]
	Prop. Mediated	1.14	[0.78, 2.11]
Heat Wave	ACME	0.14	[0.09, 0.19]
(N=869)	ADE	0.07	[0.00, 0.14]
	Total Effect	0.21	[0.14, 0.29]
	Prop. Mediated	0.66	[0.47, 0.97]

$^{*}p < 0.05$. This table presents the causal mediation analyses results for the likelihood of voting for the executive outcome which are displayed in the main analysis of the paper. This causal mediation analysis uses the regression models in Tables SI.20 and SI.22. Only respondents for whom we have outcome measures for approval of the executive's handling of the governmental crisis and all five of the executive's character traits are included (i.e., respondents with missing outcomes are excluded). We conducted this analysis with 1000 simulations. 95% confidence intervals obtained through non-parametric bootstrap procedure (percentile method).

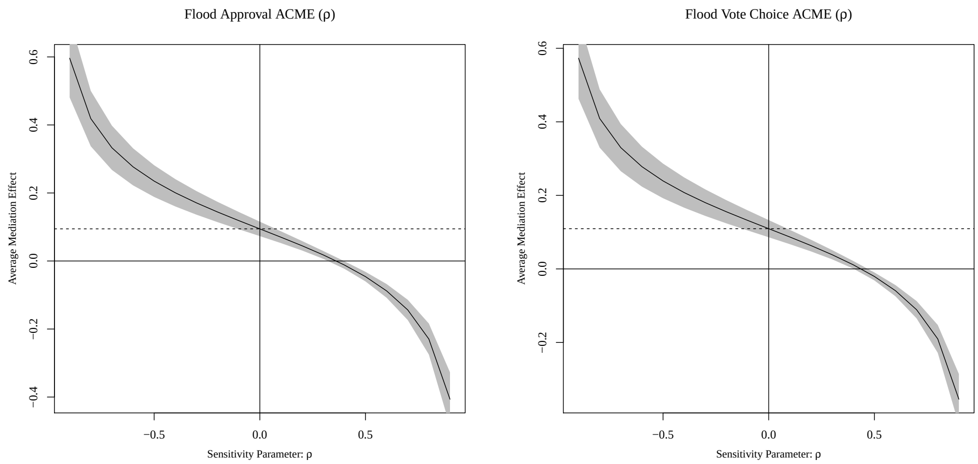

Figure SI.7: **Sensitivity Analysis of Causal Mediation Analysis for Flood Experiment (Mediated Effect of Leadership Valence).** Solid line (with 95% confidence interval) indicates ACME given any value of ρ on the interval [-1,1]. Dotted line indicates ACME when $\rho = 0$. Left and right panels present sensitivity analyses for approval and vote choice outcomes, respectively. The plots suggest that only under substantively high levels of correlation exceeding 0.4 would our estimated ACME lose statistical significance or change direction.

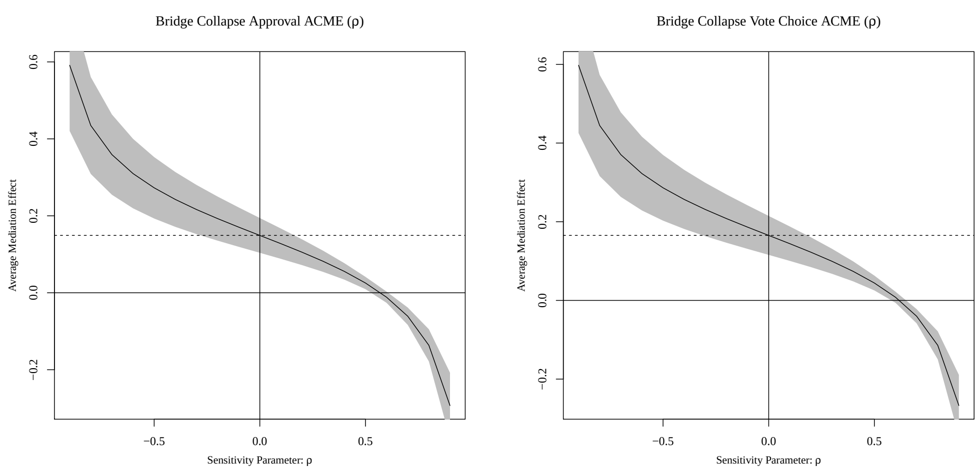

Figure SI.8: **Sensitivity Analysis of Causal Mediation Analysis for Bridge Collapse Experiment (Mediated Effect of Leadership Valence).** Solid line (with 95% confidence interval) indicates ACME given any value of ρ on the interval [-1,1]. Dotted line indicates ACME when $\rho = 0$. Left and right panels present sensitivity analyses for approval and vote choice outcomes, respectively. The plots suggest that only under substantively high levels of correlation exceeding 0.6 would our estimated ACME lose statistical significance or change direction.

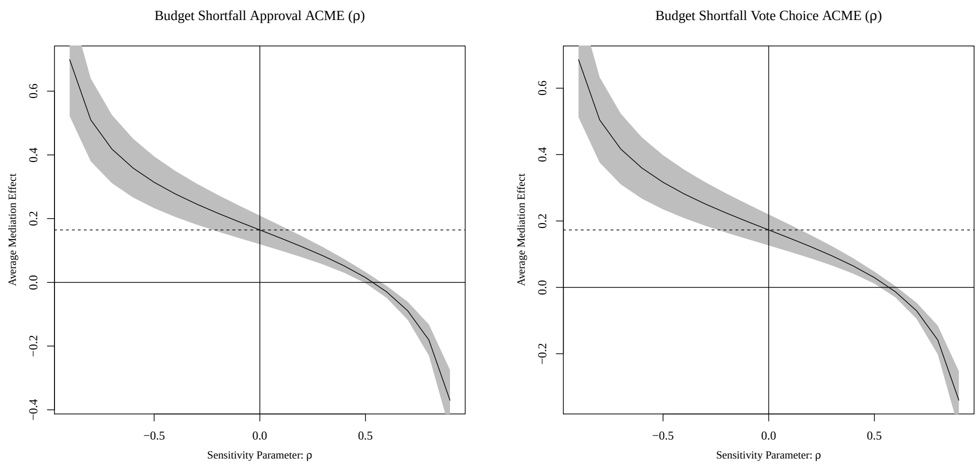

Figure SI.9: **Sensitivity Analysis of Causal Mediation Analysis for Budget Shortfall Experiment (Mediated Effect of Leadership Valence).** Solid line (with 95% confidence interval) indicates ACME given any value of ρ on the interval [-1,1]. Dotted line indicates ACME when $\rho = 0$. Left and right panels present sensitivity analyses for approval and vote choice outcomes, respectively. The plots suggest that only under substantively high levels of correlation exceeding 0.5 for our approval outcome or 0.6 for our vote choice outcome would our estimated ACME lose statistical significance or change direction.

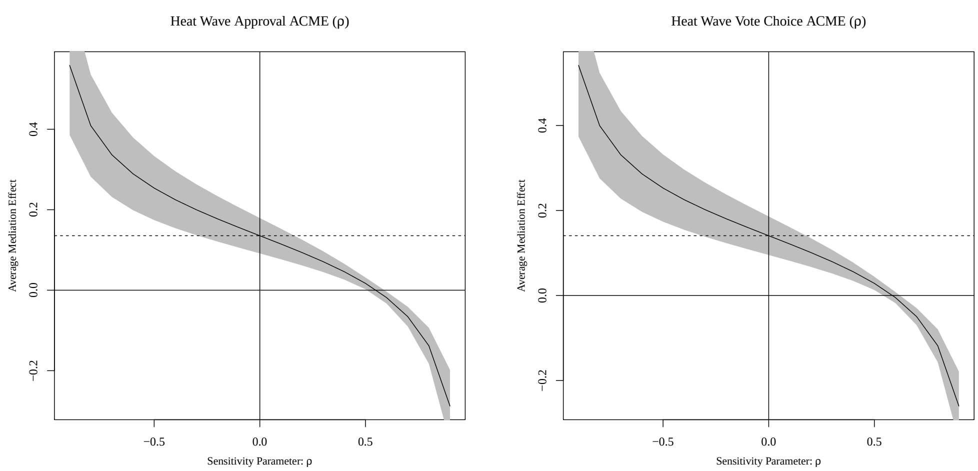

Figure SI.10: **Sensitivity Analysis of Causal Mediation Analysis for Heat Wave Experiment (Mediated Effect of Leadership Valence).** Solid line (with 95% confidence interval) indicates ACME given any value of ρ on the interval [-1,1]. Dotted line indicates ACME when $\rho = 0$. Left and right panels present sensitivity analyses for approval and vote choice outcomes, respectively. The plots suggest that only under substantively high levels of correlation exceeding 0.5 for our approval outcome or 0.6 for our vote choice outcome would our estimated ACME lose statistical significance or change direction.

Table SI.25: Causal Mediation Regressions (Blameworthiness on Treatment)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	18.89*	31.80*	46.77*	30.09*
	(0.75)	(1.52)	(1.48)	(1.50)
Blame Claim	−0.35	6.57*	4.73*	2.66
	(1.03)	(2.15)	(2.15)	(2.17)
Blame Deflect	4.69*	−0.94	−6.29*	4.36*
	(1.06)	(2.20)	(2.14)	(2.16)
R^2	0.01	0.02	0.03	0.00
Num. obs.	1938	879	879	879

$^*p < 0.05$. This table presents linear regression models of respondents' perceptions of the executives' blameworthiness regressed on their treatment conditions, which were then used in the causal mediation analysis presented in the paper. Each model uses the blame points respondents assigned to the executive (from 0 to 100) as the dependent variable, and dichotomous indicators of treatment assignment as the covariates (with the control condition as the baseline condition). The model in the first column includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.26: Causal Mediation Regressions (Approval on Treatment and Blameworthiness)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	0.33*	0.70*	0.64*	0.57*
	(0.02)	(0.03)	(0.04)	(0.03)
Blame Claim	0.23*	0.23*	0.22*	0.20*
	(0.03)	(0.04)	(0.04)	(0.04)
Blame Deflect	−0.05	−0.23*	−0.15*	−0.13*
	(0.03)	(0.04)	(0.04)	(0.04)
Blameworthiness	−0.00*	−0.01*	−0.00*	−0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.08	0.20	0.13	0.19
Num. obs.	1925	878	879	879

$^*p < 0.05$. This table presents linear regression models of respondents' approval of the executive's handling of the government crisis regressed on their treatment conditions, which were then used in the causal mediation analysis presented in the paper. All models use a dichomotous indicator of approval, coded as 1 if the respondent strongly approves or approves of the executive's handling of the governmental crisis, and coded as 0 otherwise. Covariates include dichotomous indicators of treatment assignment and a continuous measure of blame points respondents assigned to the executive. The model in the first column includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.27: Causal Mediation Regressions (Vote on Treatment and Blameworthiness)

	Flood	Bridge Collapse	Budget Shortfall	Heat Wave
Intercept	0.30*	0.54*	0.59*	0.53*
	(0.02)	(0.03)	(0.04)	(0.03)
Blame Claim	0.15*	0.20*	0.17*	0.23*
	(0.02)	(0.04)	(0.04)	(0.04)
Blame Deflect	−0.02	−0.05	−0.12*	−0.12*
	(0.02)	(0.04)	(0.04)	(0.04)
Blameworthiness	−0.00*	−0.01*	−0.00*	−0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.05	0.13	0.11	0.21
Num. obs.	1918	877	878	877

$^*p < 0.05$. This table presents linear regression models of respondents' likelihood of voting for the executive in the next election regressed on their treatment conditions, which were then used in the causal mediation analysis presented in the paper. All models use a dichomotous indicator of likelihood of voting for the executive in the next election, coded as 1 if the respondent is very likely or somewhat likely to vote for the executive, and coded as 0 otherwise. Covariates include dichotomous indicators of treatment assignment and a continuous measure of blame points respondents assigned to the executive. The model in the first column includes survey weights; results remain substantively unchanged when weights are not included.

Table SI.28: Causal Mediation Analysis—Blameworthiness and Approval

Context	Causal Quantity	Estimate	95% Confidence Interval
Flood	ACME	-0.01	[-0.02, 0.00]
(N=1925)	ADE	-0.05	[-0.13, 0.04]
	Total Effect	-0.06	[-0.13, 0.03]
	Prop. Mediated	0.15	[-0.60, 1.20]
Bridge Collapse	ACME	0.01	[-0.02, 0.03]
(N=878)	ADE	-0.23	[-0.29, -0.15]
	Total Effect	-0.22	[-0.30, -0.14]
	Prop. Mediated	-0.03	[-0.16, 0.07]
Budget Shortfall	ACME	0.03	[0.01, 0.05]
(N=879)	ADE	-0.15	[-0.22, -0.08]
	Total Effect	-0.12	[-0.20, -0.05]
	Prop. Mediated	-0.25	[-0.87, -0.07]
Heat Wave	ACME	-0.03	[-0.05, -0.00]
(N=879)	ADE	-0.13	[-0.19, -0.06]
	Total Effect	-0.15	[-0.22, -0.08]
	Prop. Mediated	0.18	[0.00, 0.38]

$^{*}p < 0.05$. This table presents the causal mediation analyses results for the approval of the executive's handling of the governmental crisis outcome which are displayed in the main analysis of the paper. This causal mediation analysis uses the regression models in Tables SI.25 and SI.26. Only respondents for whom we have outcome measures for approval of the executive's handling of the governmental crisis and the executive's blameworthiness are included (i.e., respondents with missing outcomes are excluded). We conducted this analysis with 1000 simulations. 95% confidence intervals obtained through nonparametric bootstrap procedure (percentile method).

Table SI.29: Causal Mediation Analysis—Blameworthiness and Vote

Context	Causal Quantity	Estimate	95% Confidence Interval
Flood	ACME	-0.01	[-0.03, -0.00]
(N=1918)	ADE	-0.02	[-0.11, 0.05]
	Total Effect	-0.04	[-0.12, 0.04]
	Prop. Mediated	0.38	[-5.16, 2.36]
Bridge Collapse	ACME	0.01	[-0.02, 0.03]
(N=877)	ADE	-0.05	[-0.12, 0.02]
	Total Effect	-0.04	[-0.12, 0.03]
	Prop. Mediated	-0.13	[-2.96, 3.35]
Budget Shortfall	ACME	0.03	[0.01, 0.05]
(N=878)	ADE	-0.12	[-0.19, -0.05]
	Total Effect	-0.09	[-0.17, -0.01]
	Prop. Mediated	-0.34	[-2.35, -0.07]
Heat Wave	ACME	-0.03	[-0.05, -0.00]
(N=877)	ADE	-0.12	[-0.19, -0.05]
	Total Effect	-0.15	[-0.22, -0.08]
	Prop. Mediated	0.18	[0.01, 0.40]

$^{*}p < 0.05$. This table presents the causal mediation analyses results for the likelihood of voting for the executive outcome which are displayed in the main analysis of the paper. This causal mediation analysis uses the regression models in Tables SI.25 and SI.27. Only respondents for whom we have outcome measures for approval of the executive's handling of the governmental crisis and the executive's blameworthiness are included (i.e., respondents with missing outcomes are excluded). We conducted this analysis with 1000 simulations. 95% confidence intervals obtained through nonparametric bootstrap procedure (percentile method).

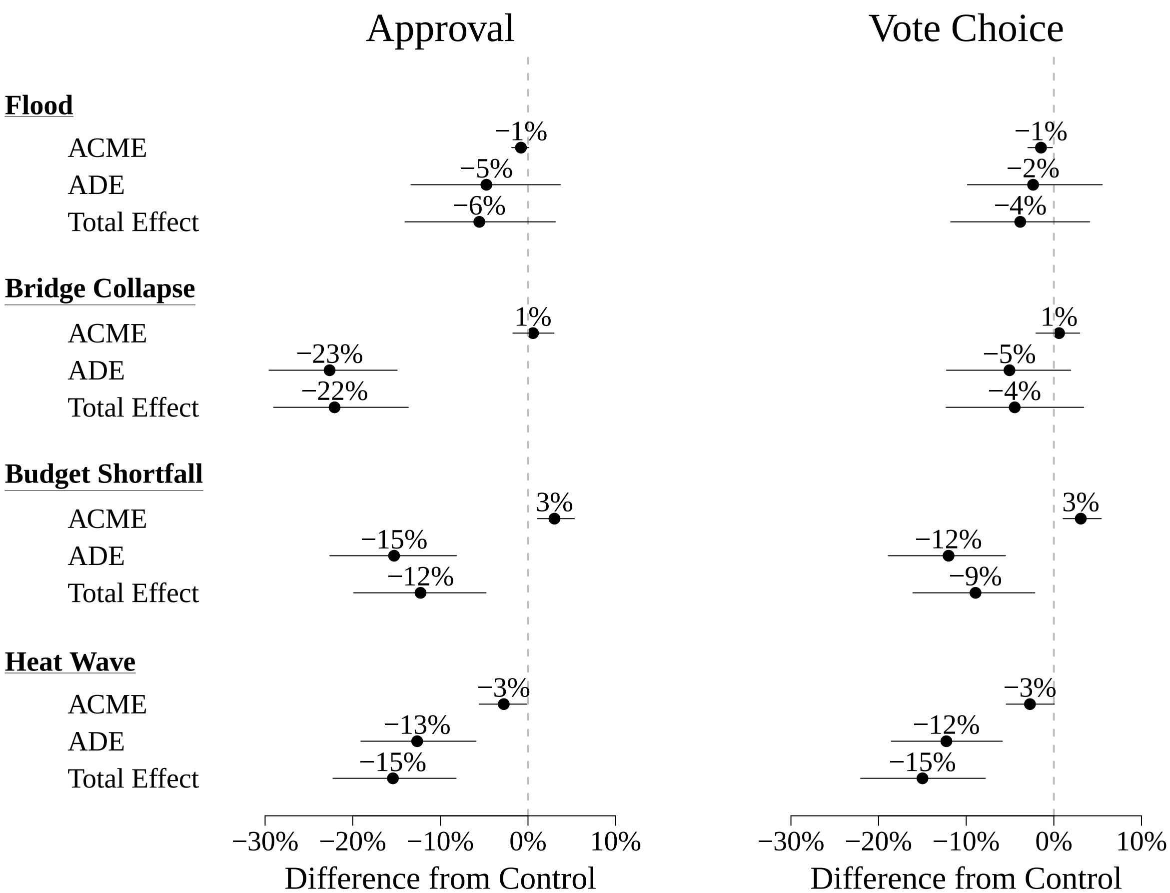

Figure SI.11: **Causal Mediation Analysis (Mediated Effect of Blameworthiness).** Estimated average causal mediation effects (ACME), average direct effects (ADE), and average total effects for respondents in the blame deflecting condition relative to respondents in the control condition across each of our four experiments. Estimates in the left and right panels correspond to the mediated and direct effects of blame deflecting for approval of the executive's handling of the crisis and likelihood of voting for the executive in the next election, respectively. Positive (negative) values along $x-$axis reflect more favorable evaluations relative to the control condition. Across all four experiments, blameworthiness, our hypothesized mediator, not only accounts for a substantively small share of the total effect, but also manifests as a significantly positive effect, a significantly negative effect, and an insignificant effect. Bars around point estimates represent 95% confidence intervals obtained through nonparametric bootstrap procedure (percentile method).

Respondent Descriptive Characteristics

In this section, we present information about the descriptive characteristics of each of our survey samples. Following suggested best practices in presenting results from experimental research (Gerber, Arceneaux, Boudreau, Dowling, Hillygus, Palfrey, Biggers, and Hendry 2014), we also conducted randomization checks for each experiment across all observed demographic characteristics. Because randomization checks are probabilistic, the presence of covariate imbalance for a small number of covariates across our experiments should be expected, and does not pose a problem for the estimation of treatment effects given that we employed a proper randomization mechanism (Gerber and Green 2012). While some scholars argue that covariate imbalance does not require any analytical adjustments (Mutz and Pemantle 2015), others suggest that we should account for imbalance in our observable demographic characteristics by including them as covariates in a regression model regressing the outcome on the treatment assignment (Gerber and Green 2012). As a conservative approach, we refit the models used in the main analysis of the paper to estimate the overall treatment effects for each experiment with all available pre-treatment covariates. These models, which are omitted here in the interest of space but are available upon request, yield substantively similar treatment effects as presented in the main body of the paper.

Table SI.30: Respondent Descriptive Characteristics

Characteristic	TAPS	MTurk (Main Analyses)	MTurk (Factorial Design)	MTurk (Flint)
Age				
18-29	7.8%	37.8%	27.4%	48.3%
30-49	26.7%	46.9%	50.2%	43.0%
50-64	31.6%	12.6%	17.3%	7.2%
65 and over	32.4%	2.6%	4.9%	1.4%
NA	1.5%	0.1%	0.1%	0.1%
Gender				
Female	51.9%	42.7%	45.8%	39.0%
Male	48.0%	57.2%	54.2%	61.0%
NA	0.1%	0.1%	0.0%	0.0%
Race/Ethnicity				
White	84.8%	75.0%	78.4%	76.3%
Black	7.7%	6.6%	6.9%	5.8%
Asian	3.1%	11.3%	7.5%	10.5%
Hispanic	10.0%	5.9%	5.3%	5.6%
Other	-	1.1%	1.8%	1.6%
NA	0.0%	0.1%	0.1%	0.2%
Education				
High school degree or less	15.1%	11.1%	10.3%	10.3%
Some college, no 4-year degree	30.3%	32.8%	33.3%	33.8%
Bachelor's degree	27.8%	44.4%	40.8%	45.5%
Post-graduate degree	26.2%	11.6%	15.6%	10.2%
NA	0.5%	0.1%	0.0%	0.1%
Income (TAPS)				
Less than $30,000	19.2%	-	-	-
$30,000-$60,000	27.5%	-	-	-
$60,000-$90,000	21.0%	-	-	-
$90,000-$125,000	16.0%	-	-	-
More than $125,000	12.6%	-	-	-
NA	3.7%			
Income (MTurk)				
Less than $25,000	-	16.7%	18.0%	20.8%
$25,000-$50,000	-	33.2%	33.6%	32.7%
$50,000-$75,000	-	24.5%	23.6%	23.0%
$75,000-$100,000	-	12.5%	13.6%	11.6%
$100,000-$200,000	-	11.6%	9.2%	10.6%
$200,000 or more	-	1.3%	1.8%	1.2%
NA	-	0.2%	0.1%	0.1%
Party Identification				

Characteristic	TAPS	MTurk (Main Analyses)	MTurk (Factorial Design)	MTurk (Flint)
Democrat	37.1%	46.9%	42.8%	44.3%
Independent	29.1%	30.5%	31.1%	34.4%
Republican	25.7%	19.6%	23.1%	18.7%
Other	5.7%	3.0%	3.1%	2.6%
NA	2.4%	0.1%	0.0%	0.0%
Ideology				
Liberal	32.0%	50.9%	48.4%	54.5%
Moderate	23.7%	25.3%	24.3%	24.4%
Conservative	37.0%	23.8%	27.3%	21.1%
Other	7.0%	-	-	-
NA	0.4%	0.1%	0.0%	0.0%

This table indicates the percentage of respondents in each sample (denoted by the column headings) who reported each demographic characteristic (denoted by the row labels). The TAPS and MTurk (Main Analyses) samples are those used for the set of experiments on four governmental crises in the main text. The MTurk (Factorial Design) sample is that used for the set of factorial experiments presented in the Supplemental Information that include information about the elected executives' partisanship and the crises' severity. The MTurk (Flint) sample is that used for the experiment featuring the Flint, Michigan water crisis in the main text.

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