Online Appendix: Assessing the Breadth of Framing Effects

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Appendix: Prior Framing Experiments

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Table 1: This table presents a summary of dependent variables for select, prominent framing studies. It also indicates whether each study explicitly estimates spillover effects on more distant issues.

	Issues Covered by Dependent Variables	Estimates Spillover?
1. Nelson, Clawson, and Oxley (1997)	KKK rally	No
2. Nelson, Oxley, and Clawson (1997)	Welfare policy	No
3. Nelson and Oxley (1999)	Land management	No
	Welfare reform	
4. Haider-Markel and Joslyn (2001)	Concealed handguns	No
	Columbine	
5. Druckman (2001)	Spending on poor	No
	KKK rally	
6. Druckman and Nelson (2003)	Campaign finance	No
7. Druckman (2004)	Community grants	No
	Disease prevention	
	Employment policy	
	Youth crime	
8. Chong and Druckman (2007)	Urban growth	No
	Hate group rally	
9. Slothuus and De Vreese (2010)	Welfare reform	No
	Trade policy	
10. Chong and Druckman (2010)	Patriot Act	No
	Urban growth	
11. Druckman and Bolsen (2011)	Carbon nanotubes	Yes
	Genetically modified food	
12. Arceneaux (2012)	Disease prevention	No
	HS gay-straight club	

Arguments

Security Frame

- The September 11th attacks and the news that al-Qaeda was planning new attacks on U.S. soil show how vulnerable America still is to terrorists. Innocent people can be killed while traveling to visit family or going to work. Across the country, we have to do everything we can to reduce the threat of terrorism. We have to stop terrorists before they act. This means conducting more frequent searches of suspicious people boarding planes, trains, subways, and buses.

- As the recent killings in Arizona remind us, America is very vulnerable to violent crime. Innocent people can be killed in their front yards. Across the country, we have to do everything we can to reduce the threat of violent crime. We have to stop violent criminals before they act. This means cracking down on the smaller offenses that all too often lead to violent crime, and making sure that convicted criminals always serve out their full sentences.

Lack of Trust Frame

- With a recession as deep as this one, there are more than 10 million unemployed Americans, and it's going to take years for our economy to recover. In February 2009, the government in Washington made things worse by passing an $800 billion stimulus package, which is more than $2,500 for every person living in this country. Now, it looks like a lot of that money didn't help the economy. Unemployment is still very high. The money went to pork-barrel projects and federal bureaucrats rather than creating jobs for unemployed Americans. The government in Washington can't even balance its own budget. How can we trust it to spend so much taxpayer money?

- Health care is one of the most complicated issues we face. It involves 1 of every 6 dollars spent here in the United States. The health care system includes millions of doctors and nurses and thousands of hospitals and clinics. Together, they regularly make decisions that can mean life or death. The government in Washington can't even balance its own budget. How can we trust it to run something as complicated as the health care system?

Data Set Structure

Here are the first 20 rows of the data. Each respondent-DV-round gets a row. The "treat" column displays the frame that is serving as the treatment in a given row. "Round" refers to whether we are considering the first frame or the second frame as the treatment. The outcome score is displayed in the "score" column. Also, if the DV was asked prior to the frame in that row being shown, (as conveyed by the "q.ord" variables), "score" gets an NA.

	CaseID	frame	q1.ord	q2.ord	q3.ord	q4.ord	q5.ord	DV	score	treat	round
1	3	crime	terror	health	stim	crime	poor	CRMSPND	50.00000	crime	1
3319	3	crime	terror	health	stim	crime	poor	TRRSPND	16.66667	crime	1
6637	3	crime	terror	health	stim	crime	poor	POORSPND	50.00000	crime	1
9955	3	crime	terror	health	stim	crime	poor	HLTHSPND	33.33333	crime	1
13273	3	crime	terror	health	stim	crime	poor	STIMSPND	50.00000	crime	1
16591	3	stim	terror	health	stim	crime	poor	CRMSPND	50.00000	stim	2
33191	3	stim	terror	health	stim	crime	poor	TRRSPND	16.66667	<NA>	2

66371	3	stim	terror	health	stim	crime	poor	POORSPND	50.00000	stim	2
99551	3	stim	terror	health	stim	crime	poor	HLTHSPND	33.33333	<NA>	2
132731	3	stim	terror	health	stim	crime	poor	STIMSPND	50.00000	stim	2
2	4	NOT ASSIGNED	crime	terror	health	stim	poor	CRMSPND	83.33333	NOT ASSIGNED	1
3320	4	NOT ASSIGNED	crime	terror	health	stim	poor	TRRSPND	33.33333	NOT ASSIGNED	1
6638	4	NOT ASSIGNED	crime	terror	health	stim	poor	POORSPND	50.00000	NOT ASSIGNED	1
9956	4	NOT ASSIGNED	crime	terror	health	stim	poor	HLTHSPND	33.33333	NOT ASSIGNED	1
13274	4	NOT ASSIGNED	crime	terror	health	stim	poor	STIMSPND	33.33333	NOT ASSIGNED	1
21000	4	NOT ASSIGNED	crime	terror	health	stim	poor	CRMSPND	83.33333	NOT ASSIGNED	2
33201	4	NOT ASSIGNED	crime	terror	health	stim	poor	TRRSPND	33.33333	NOT ASSIGNED	2
66381	4	NOT ASSIGNED	crime	terror	health	stim	poor	POORSPND	50.00000	NOT ASSIGNED	2
99561	4	NOT ASSIGNED	crime	terror	health	stim	poor	HLTHSPND	33.33333	NOT ASSIGNED	2
132741	4	NOT ASSIGNED	crime	terror	health	stim	poor	STIMSPND	33.33333	NOT ASSIGNED	2

Additional Results

Table 2: This table summarizes the five spending variables for the 861 respondents assigned to the control group. Each variable ranges from 0 to 100 and is coded such that 100 is in the direction of the corresponding argument.

	Mean	SD
Increase Anti-Crime Spending	56.00	20.72
Increase Anti-Terror Spending	43.52	24.44
Decrease Anti-Poverty Spending	44.13	27.30
Decrease Health Care Spending	41.75	29.34
Decrease Stimulus Spending	48.10	32.60

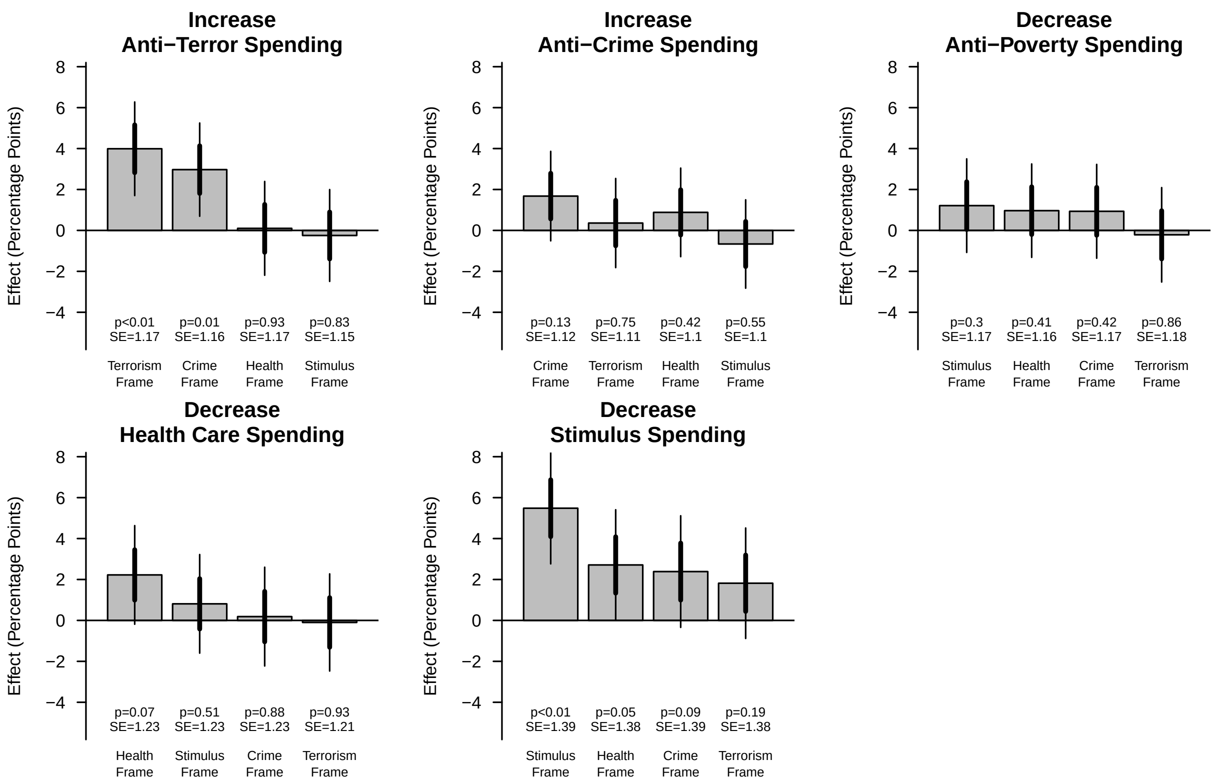
Assessing the Arguments' Strength

One important question is about the arguments' relative strength, as it is possible that stronger arguments will have broader effects. Accordingly, Table 3 presents the share of all respondents who deemed the first argument "convincing" in response to the open-ended question. As the table makes clear, the four arguments are all perceived as convincing by a majority of respondents, although the crime argument appears to be the weakest, with just a slim majority saying that it is convincing. As a point of comparison, in the table's third column, we present the estimated effects of each argument on spending preferences on that issue, effects whose estimation is described below. As the table makes clear, there is not a strong relationship between the arguments respondents found convincing and those that moved attitudes. For one thing, the health care argument is seen as very convincing, yet the attitudinal shift it induces is comparatively small, perhaps because of the entrenched partisan divisions on health care. Still, each of the four arguments worked in the sense that it moved issue preferences in the expected direction.

Table 3: This table reports the share of respondents who were exposed to each argument first who found that frame to be convincing. It also indicates the effect of each argument on spending preferences on that issue controlling for party ID, with spending preferences coded to vary from 0 to 100.

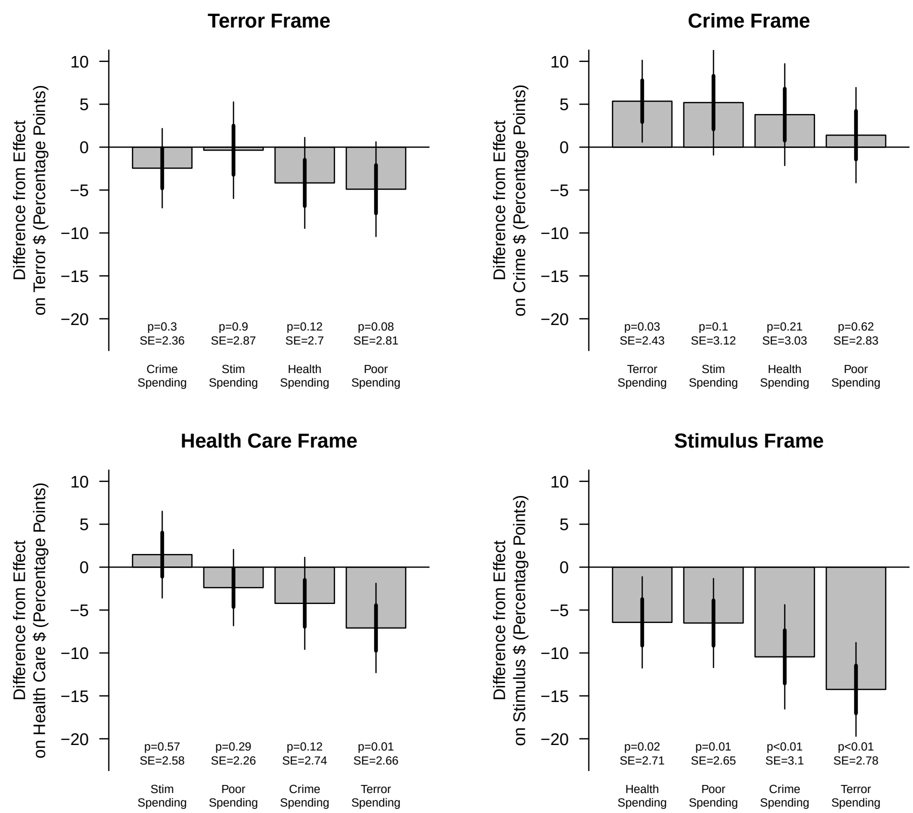
	% Convincing	Within-Issue Effect
Crime Argument	51.3	1.68
Terrorism Argument	59.7	3.99
Stimulus Argument	66.7	5.48
Health Argument	66.9	2.22

Figure 1: *Effects of four arguments on spending preferences.*



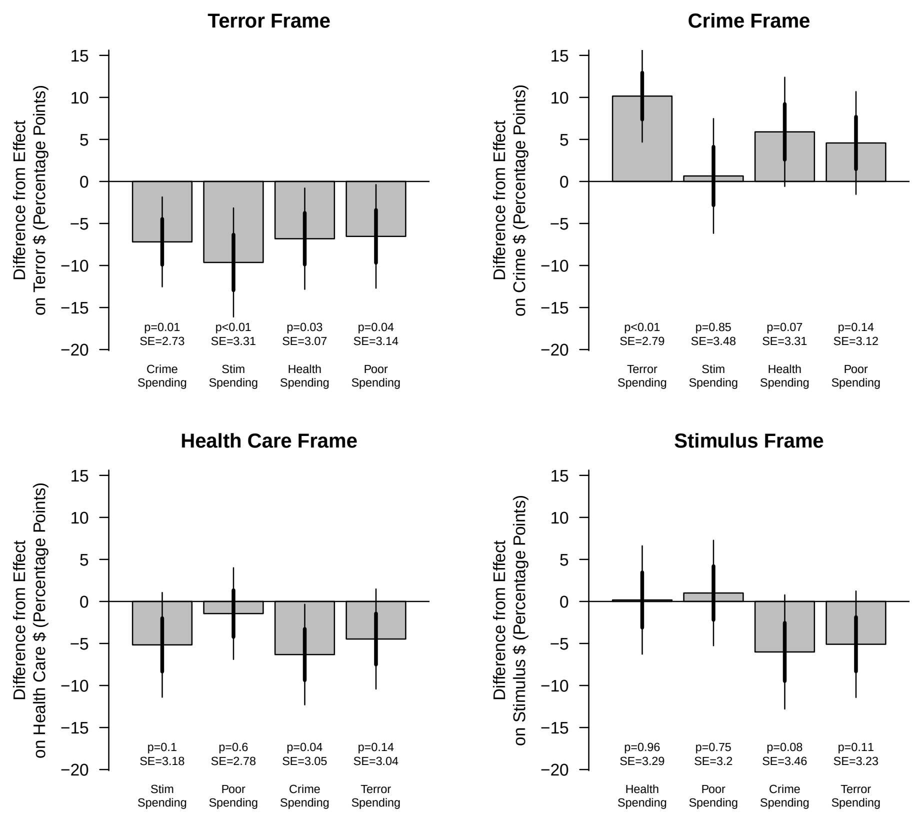
This figure illustrates the effect of each frame/argument on each of the five spending areas as compared to an 861-person control group that was not exposed to any arguments. The treatment groups vary slightly in size, but average 983 respondents. The gray bars indicate mean effects on spending scales ranging from 0 to 100, while the vertical lines indicate 95% confidence intervals. Under each bar, we report the corresponding two-sided p-values and standard errors.

Figure 2: *Relative effects of frames on attitudes reported immediately following exposure.*



This figure reports the difference-in-difference results when we narrow the definition of "treated" to include only respondents who saw the frame in question first and then assessed the relevant spending question without reading any intervening frames. All observations from those assigned to see no argument are retained. The gray bars indicate the mean difference-in-difference estimate. The corresponding two-sided p-values and standard errors are listed below each estimate. The thick vertical lines indicate standard errors, while the thin lines indicate 95% confidence intervals.

Figure 3: *Relative effects of frames on attitudes reported immediately following exposure.*



This figure reports the results when we narrow the definition of "treated" to include only respondents who saw the frame in question first and answered a given spending question in the first or second out of five positions. Unlike the models used to estimate Figure 2, responses from the third, fourth and fifth positions were also excluded for those assigned to control. The gray bars indicate the mean difference-in-difference estimate. The corresponding two-sided p-values and standard errors are listed below each estimate. The thick vertical lines indicate standard errors, while the thin lines indicate 95% confidence intervals.

Pooled Results

The results in the main manuscript provide an issue-by-issue look at frames' capacity to influence attitudes at varying degrees of distance from the frame's content. Here, we conduct tests which pool across the different issues to provide an overall assessment of the breadth of framing effects. To do so, we must first categorize each argument-attitude pairing based on the fit or distance between them. We then pool across the relevant pairings, exploiting the fact that all of the spending preferences were measured on the same scale.

Specifically, we estimate three quantities of interest, all of which are differences in treatment effects across the experimental conditions. The first compares the effect of arguments on directly related outcomes (e.g. the terrorism argument and anti-terror spending) with the effect of arguments on distant or seemingly unrelated outcomes (e.g. the terrorism argument and health care spending). The second estimates the effect of arguments on directly related outcomes versus the effect of arguments on proximate outcomes for which the frame still applies even though the issue differs (e.g. the terrorism argument and anti-crime spending). The third comparison is between the effect of arguments on a proximate outcome and the effect of arguments on the two most distant outcomes jointly (e.g. the terror argument and health care/ stimulus spending).[1] Table 4 displays the various definitions of distance used for these tests. Given the content and structure of the frames, terrorism and crime are considered proximate issues, as are health care and economic stimulus.

Table 4: This table presents the classification of argument-spending attitude pairings for the pooled tests. The rows denote the argument in question while the columns indicate the distance between the frame and the outcome of interest.

Argument	Direct	Proximate	Distant (a)	Distant (b)
Terror	Anti-terror	Crime	Stimulus	Health Care
Crime	Crime	Anti-terror	Stimulus	Health Care
Health Care	Health care	Stimulus	Anti-terror	Crime
Stimulus	Stimulus	Health Care	Anti-terror	Crime

Our three quantities of interest are differences in treatment effects (i.e. differences-in-differences). To estimate each of these quantities, we generated indicator variables in our long-form data set (in which each row represents a respondent-argument-outcome triad), for whether the conditions above were met. For example, to compare the effect of direct frames to distant ones, we generated a "direct" indicator that took a 1 if the argument being offered directly related to the spending outcome being measured (e.g. a crime argument and crime spending) and a zero if no argument was offered and the same spending outcomes were measured. We employed the analogous coding for the "distant" indicator. Spending outcomes which did not fit the definition of either pooled conditions (e.g. anti-poverty spending) were omitted. We then estimated the following least squares model with respondent-clustered standard errors:

[1] In most cases, assessing the distance between frame topics and outcome topics was straightforward, but some subjectivity was unavoidable in identifying the "most distant" frames. For this reason, we estimated two versions of the "most distant frame" tests, and expect roughly similar results in each.

$$Score = \alpha + \beta_1 direct + \beta_2 distant + \mathbf{Z}\gamma + \epsilon$$

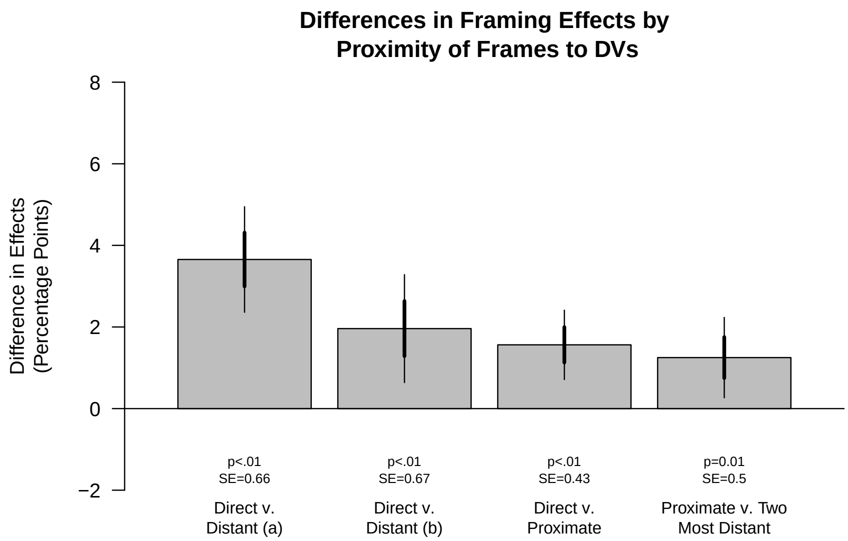
where Y is a vector of responses to various spending outcomes, α is an intercept, *direct* is an indicator for being in the "direct" condition, *distant* is an indicator for being in the "distant" condition, $\mathbf{Z}$ is a vector of party ID indicators to improve efficiency, and ϵ is an error term. The control condition was omitted as a reference category. The average difference in responses after seeing a directly related frame vs. seeing no frame is therefore represented by β_1; the average difference in responses after seeing an unrelated (i.e. distant) frame vs. seeing no frame is represented by β_2; and the difference-in-differences, (the quantity of interest), is simply $\beta_1 - \beta_2$. The standard error for the difference-in-difference, SE_{DID}, was computed analytically as:

$$\widehat{SE}_{\widehat{DID}} = \sqrt{\widehat{Var}_{\widehat{\beta_1}} + \widehat{Var}_{\widehat{\beta_2}} - 2 * \widehat{Cov}_{\widehat{\beta_1},\widehat{\beta_2}}}$$

We performed an analogous procedure to estimate the other aforementioned differences-in-differences (i.e. direct vs. proximate and proximate vs. two most distant).

As the two bars on the left side of Figure 4 show, the strongest differences in framing effects appear when comparing the effects of same-issue frames with the effects of distant-issue frames. The differences in treatment effects are 3.65 and 1.96 percentage points on the spending scales, and are fairly precisely estimated even after adjusting for within-respondent clustering ($p < 0.01$ for both estimates). The third vertical bar from the left shows that the same-issue frames are also stronger in their average effects than are frames which are structurally related to the spending attitude being asked about, though the difference shrinks to 1.56 percentage points ($p < 0.01$). The arguments on related issues also appear to have slightly stronger effects than the arguments on more distant issues, with a difference of 1.25 percentage points ($p = 0.01$). Overall, there is some evidence of spillover, but also very clear evidence that frames are more influential for attitudes on the issues to which they directly pertain.

Figure 4: *Relative effects of arguments on spending attitudes by argument-attitude distance.*



This figure illustrates the pooled effects of the four arguments on attitudes that vary in their distance from the issue and frame. The effects were estimated by pooling argument-attitude pairings at similar levels of distance and then comparing them to the control group that was exposed to no arguments. The gray bars indicate the mean differential effect, while the thick vertical lines show standard errors and the thin vertical lines show 95% confidence intervals. The corresponding two-sided p-values and standard errors are listed under each bar.