Negativity Biases and Political Ideology: A Comparative Test Across 17 Countries

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Abstract:
There is a considerable body of work across the social sciences suggesting negativity biases in human attentiveness and decision-making. Recent research suggests that individual variation in negativity biases is correlated with political ideology: persons who have stronger physiological reactions to negative stimuli, this work argues, hold more conservative attitudes. Such results have mostly been encountered in the US, however. Does the link between psychophysiological negativity biases and political ideology apply elsewhere? We answer this question with the most extensive cross-national psychophysiological study to date. Respondents across 17 countries and six continents were exposed to negative and positive televised news reports and static images. Sensors tracked participants' skin conductance, and a survey captured their left-right political orientation. Analyses performed at three levels of aggregation – respondent-as-a-case, stimuli-as-a-case, and second-by-second time-series – fail to find strong support for the link between negativity biases and political ideology.

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Online Appendix

Contents

1. Details on the Fielding of Each Experiment

Brazil: A diverse sample was recruited by local research assistants among their acquaintances, aiming for diversity in terms of age, education, and political orientation. Experiments were run in a hotel meeting room in Brasilia in 2016.

Canada: Our primarily English-language sample, students recruited through posters and emails, was collected in 2013, in a purpose-built lab at McGill University in Montréal. Our primarily French-language sample, recruited among participants in two non-student online studies, was collected in 2015, in a faculty office at the Université de Montréal.

Chile: A representative (non-student) sample was provided by the Centre for Experimental Social Science (CESS) Santiago, and conducted in their purpose-built lab in Santiago in 2016.

China: A diverse (non-student) sample was provided by the lab at Nankai University in Tianjin, based on (a) a respondent pool at the university, and (b) access to workers at a local IT firm. Experiments were run in 2018 at either a purpose-build lab at Nankai University, or offices at the IT firm.

Denmark: A diverse (non-student) sample was recruited by local research assistants among their acquaintances, aiming for diversity in terms of age, education, and political orientation. Experiments were run in faculty offices at Aarhus University in 2016.

France: We rely on a sample built through posters and snowball sampling, at Sciences Po in Paris. Experiments were run in faculty offices at that university in 2015. A second round of experiments was completed in 2017 in the same location to diversify the sample – in particular, we sought to recruit participants from the right side of the political spectrum, and from a more diversified age range and educational background.

Ghana: A diverse (non-student) sample was provided in collaboration with the Centre for Experimental Social Science (CESS), working with Central University, Accra. Experiments were run in classrooms at Central University in 2017.

India: A representative (non-student) sample was provided by the Centre for Experimental Social Science (CESS) at FLAME University. Most experiments were conducted in their purpose-built lab in Pune in 2017, but a limited number were run in a nearby construction compound.

Israel: Our primarily Jewish sample relies on a student participant pool at the Hebrew University in Jerusalem. Experiments were run in a purpose-built lab at that university in 2013. Our primarily Palestinian sample relies on a student participant pool, supplemented with snowball sampling, at the University of Haifa. Experiments were run in a purpose-built lab at that university in 2016.

Italy: We rely on a student sample, built through posters and emails at the University of Milan. Experiments were run in a small quiet room at that university in 2016.

Japan: We rely on a student sample, built through an existing participant pool as well as emails at Waseda University in Tokyo. Experiments were run in two small quiet rooms at that university in 2016.

New Zealand: A representative (non-student) sample was provided by the Vote Compass. Experiments were run in a conference room at the Victoria University of Wellington in 2016.

Russia: A diverse (non-student) sample was recruited by a local research assistant among acquaintances, aiming for diversity in terms of age, education, and political orientation. Experiments were run in a hotel meeting room in St-Petersburg in 2017.

Senegal: A diverse (non-student) sample was gathered by local research assistants among their acquaintances, aiming for diversity in terms of age, education, and political orientation. Experiments were run in hotel conference rooms in Dakar in 2017.

Sweden: A representative (non-student) sample was provided by the Citizen Panel. Experiments were run in conference rooms at the University of Gothenburg in 2015.

UK: A representative (non-student) sample was provided by the Centre for Experimental Social Science (CESS) at Nuffield College, and conducted in their purpose-built lab in Oxford. Experiments occurred in two rounds, first in 2015 and then in 2017.

US: Most experiments were conducted in a purpose-build lab at the University of Michigan in Ann Arbor in 2015-2016. We collected three different samples: one student sample based on an existing participant pool, another student sample based on posters and snowball sampling, and a representative sample built through quota sampling from an existing medical-experimental pool. Additional US experiments were conducted in a lab at Texas A&M.

2. Stimuli

Photos (with IAPS reference numbers): disgusting (3059, 7380, 9300, 9325), threatening (1202, 2683, 3530, 6260, 6510), neutral (5500,7010, 7030, 7040, 7080), positive (1500, 2058, 5202, 5260, 7330).

3. Processing of Physiological Data

Our research requires that we are able to conduct experiments in various locations, and not necessarily in a traditional lab environment. It is for this reason that we rely on a portable encoder from Thought Technologies (http://thoughttechnology.com); specifically, we rely on either a FlexComp or ProComp5 Infiniti system, alongside a Skin Conductance Sensor. This system is connected to a computer via USB cable.

We record the raw signal (at 256/second), and process the resulting data in R. The processing of galvanic skin levels is relatively straightforward: we smooth the raw signal using a rolling average, with slightly larger weights attributed to the middle three values. In R, the script is as follows: scl <- filter(scl, filter = c(1/8, 1/4, 1/4, 1/4, 1/8), sides=2). This serves to remove much of the noise in the series, although it does not entirely erase the impact of outlying values. This is by design; but note that a series in which we entirely remove outlying values has no significant impact on our results. (We are not focusing on the millisecond-by-millisecond reactions to brief stimuli, after all, but rather on SCL over rather long intervals.) Most of our analyses rely on a down-sampled version of this smoothed signal, by one-second intervals, or by stimulus (video, or photo).

The reliability of the data for every respondent is verified by hand. As is typical in physiological experimentation, there are respondents for whom physiological measures were not captured reliably, due in part to equipment failures (such as cables becoming disconnected). For this reason, results in the paper are based on somewhat less than the full 1,152 participants. Exclusion was based on looking at diagnostic figures of skin conductance for each respondent. This was done by the authors, and independently by research assistants not involved in the analysis. 19.3% of cases were excluded.

4. Measurement of Political Ideology

The scale based on Wilson-Patterson is standardized to run from 0 to 1. Liberals are at the low end, and conservatives are at the high end. Scores are based on responses (disagree / unsure / agree) to a list of issues. Below is the subset of issues that coalesce among each sample (R means reversed coding), along with the alpha score of the reliability analysis in brackets (results using the complete sample before data processing are very similar).

Brazil: abortion (R), capitalism, gay marriage (R), gun control (R), military spending, patriotism, socialism (R) [.64].

Canada: abortion (R), capitalism, censorship, death penalty, gay marriage (R), military spending, obedience, patriotism, socialism (R), and tax cuts [.80].

Chile: abortion (R), capitalism, censorship, death penalty, gay marriage (R), immigration (R), military spending, obedience, patriotism, and socialism (R) [.75].

China: censorship, obedience, patriotism, and women's equality (R) [.36].

Denmark: capitalism, death penalty, gun control (R), immigration (R), military spending, obedience, pollution control (R), socialism (R), and tax cuts [.63].

France: capitalism, censorship, death penalty, gay marriage (R), immigration (R), military spending, obedience, patriotism, pollution control (R), socialism (R), tax cuts, and women's equality (R) [.77].

Ghana: death penalty, gay marriage (R), obedience, patriotism, and tax cuts [.37].

India: abortion (R), censorship, death penalty, gay marriage (R), military spending, obedience, patriotism, and tax cuts [.70].

Israel (jewish): abortion (R), censorship, gay marriage (R), immigration (R), military spending, and women's equality (R) [.67].

Israel (palestian): abortion (R), death penalty, gay marriage (R), immigration (R), military spending, patriotism, and socialism (R) [.57].

Italy: abortion (R), capitalism, censorship, death penalty, immigration (R), military spending, obedience, patriotism, pollution control (R), and women's equality (R) [.67].

Japan: capitalism, censorship, death penalty, gay marriage (R), immigration (R), obedience, patriotism, and women's equality (R) [.65].

New Zealand: capitalism, censorship, death penalty, gay marriage (R), military spending, obedience, patriotism, pollution control (R), socialism (R), and tax cuts [.76].

Russia: abortion (R), censorship, gay marriage (R), obedience, patriotism, and tax cuts [.78].

Senegal: censorship, obedience, patriotism, and tax cuts [.40].

Sweden: capitalism, death penalty, gay marriage (R), gun control (R), immigration (R), military spending, obedience, patriotism, socialism (R), and tax cuts [.83].

UK: abortion (R), capitalism, censorship, gay marriage (R), immigration (R), military spending, obedience, patriotism, tax cuts, and women's equality (R) [.71].

US: abortion (R), capitalism, death penalty, gay marriage (R), gun control (R), immigration (R), military spending, obedience, patriotism, pollution control (R), socialism (R), and tax cuts [.78].

Note that we also consider the 11-point scale asking respondents to place themselves on a left-right continuum. Figure A1 shows each sample divided into those who identified as left (<5), center (=5) and right (>5). This figure offers evidence of the breadth of ideological positions in each sample.

5. Control Variables

Age (18-74): years since birth.

Income (0-1): 0 = much lower than country average, .5 = average, 1 = much higher than country average.

University (0/1): 0 = no university education, 1 = university education.

Woman (0/1): 0 = man, 1 = woman.

6. Power Calculations

While the pooled (cross-national) analysis has a large number of cases, there are reasons to be concerned about whether country-by-country analyses are sufficiently powered. We do not present country-by-country analyses from the individual-level data, only pooled results (in Tables 2 and 5). This is partly due to the reduced number of participants in country-specific models. Nevertheless, we consider some issues of power here, focused on the simple individual-level data, and relying on Cohen's work on statistical power analysis as implemented using the *pwr* package in R.

Using a power test for a general linear model with five independent variables (as in Table 2), the 'small' effect size suggested by Cohen (.02), a power of 80%, and statistical significance of $p < .05$, suggests that we would need roughly 628 participants in order to reveal a small but significant effect. We clearly pass this threshold in the pooled results of Tables 2 and 5, but we would not do so in individual-level, by-country estimations (where Ns range between roughly 30 and 70). That said, the seminal work by Dodd et al. (2012) relies on just 46 participants and finds an R-squared of .39 where ideology is regressed on a variable capturing difference in skin conductance alongside demographic controls (age, gender, income and education, though note that with the exception of education, the demographic controls are statistically insignificant). If we substitute that effect size into a power calculation that is otherwise unchanged, the estimated required sample size is just 19. Were our effects as large as in the Dodd et al. (2012) paper, it would not appear as though our by-country results would be under-powered.

That said, it is not entirely clear that we should expect effects of a similar magnitude to what is found in the Dodd et al. (2012) analysis. We use videos rather than photos; and then slightly different photos. We also use skin conductance as a LHS variable with ideology on the RHS. So let us consider a power calculation with more moderate expectations: 50 participants, and an expected R-squared that is just .20. The estimated power in this instance is .79. We thus are reasonably confident that our sample-specific estimations are not under-powered in the analyses using stimulus-level data and time-series data, at least when using the Dodd et al. (2012) findings as our prior. Of course, we can take priors into account in another way as well, and that is the focus of the section that follows.

7. Bayesian Analysis

The preceding results fail in most instances to reject the null hypothesis; that is, we are generally unable to reject the null hypothesis that negativity biases are unrelated to political ideology. We rely on frequentist statistics for all of our analyses, but particularly given our null results, there are good reasons to consider using a Bayesian approach. First and foremost, a frequentist analysis can fail to reject the null hypothesis (based on a largely arbitrary cutoff), while a Bayesian analysis can speak to the likelihood of the null hypothesis compared to the alternative hypothesis. (For a general discussion of Bayesian methods in social science see, e.g., Jackman 2009.)

A Bayesian analysis also allows us to take into account past findings, insofar as we can use past findings to establish the priors used in a Bayesian model. The importance of these priors to an estimation with a large number of cases will be limited, admittedly. A more important difficulty in this instance is that it is not at all clear what priors to use. On the one hand, work by Dodd et al. (2012) suggests that we should expect a moderate-to-strong relationship between ideology and negativity biases. On the other hand, recent work has failed to replicate that finding (Bakker et al. N.d.; Osmundsen et al. N.d.).

Even so, it is possible to consider the likelihood of the null hypothesis with varying priors. Based on the vast body of work connecting ideology to demographics, we expect a weak negative relationship between gender and right-wing ideology (coef.=-.1), and a weak negative relationship between university education and ideology (coef.=-.1). These are both binary variables, so in the absence of other strong priors, we estimate roughly the same magnitude for each effect. We also expect a weak positive relationship between income and ideology (coef.=.05), and our expectation for income takes into account the variable's 7-point scale. We expect a weak positive relationship between age and ideology (coef.=.01), and our expectation for age takes into account the fact that it is measured in years.

Our prior for ideology varies across models. It is informed in part by Dodd et al. (2012), even as they use ideology as a LHS variable, and rely on a different measure of ideology. We explore results based on several possibilities, where the coefficient for ideology ranges from 0 through 4 (where 2.8, for instance, would be roughly equivalent to a one-standard-deviation change in political ideology being associated with a one-standard-deviation change in the negativity-bias measure; though we recognize that a Bayesian prior is ideally not defined by the data used in the estimation).

Changes in priors make little difference to the estimated distributions of coefficients. In each estimation, the coefficient for ideology is roughly .106 with a standard error of .093, very similar to what we have seen in the OLS models in the paper (such as Table 2). More useful perhaps is the estimation of Bayes Factors, comparing each model including ideology to a model which includes the demographics but excludes ideology. The Bayes Factors range from 24.6 (when the prior for ideology is 0) to 54.2 (when the prior for ideology is 4), suggesting that the model without ideology is roughly 25 to 54 times more likely than a model that includes ideology. There is thus very strong evidence to support the null hypothesis (where the video-based study is concerned).

References

Bakker, Bert, Gijs Schumacher, Claire Gothreau, & Kevin Arceneaux. (N.d.) "Conservatives and Liberals have Similar Physiological Responses to Threats: Evidence from Three Replications." Forthcoming in *Nature Human Behaviour*.

Dodd, Michael D., Amanda Balzer, Carly M. Jacobs, Michael W. Gruszczynski, Kevin B. Smith, & John R. Hibbing. 2012. "The Political Left Rolls with the Good and the Political Right Confronts the Bad: Connecting Physiology and Cognition to Preferences." *Philosophical Transactions of the Royal Society of London B: Biological Sciences* 367(1589): 640-649.

Jackman, Simon. 2009. *Bayesian analysis for the social sciences*. Vol. 846. John Wiley & Sons.

Osmundsen, Mathias, David Hendry, Lasse Laustsen, Kevin Smith, & Michael Bang Petersen. (N.d.) "The Psychophysiology of Political Ideology: Replications, Reanalysis, and Recommendations." Forthcoming in *The Journal of Politics*.

Figure A1. Self-Reported Political Ideology

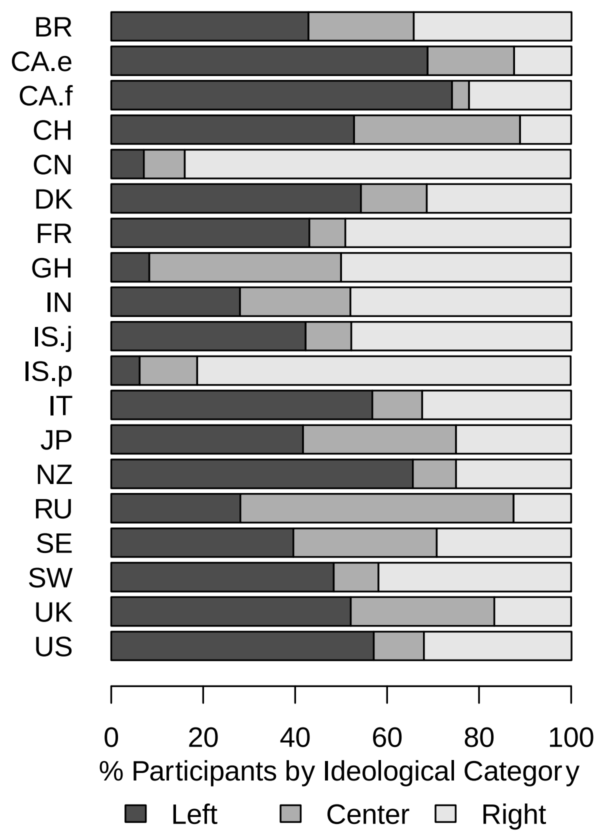

Table A1. Sample Details (Means and Standard Deviations)

	N	Age (18-74)	Female (0/1)	Income (0-1)	University (0/1)	English Proficiency (1-7)	Ideology (0-1)
Samples pooled	933	29.2 (12.2)	.53 (.50)	.54 (.24)	.66 (.47)	5.4 (1.9)	.39 (.23)
Brazil	35	25.6 (5.7)	.57 (.50)	.56 (.23)	.69 (.47)	4.1 (2.1)	.36 (.19)
Canada (English)	32	22.9 (4.4)	.69 (.47)	.51 (.25)	.88 (.34)	6.8 (.6)	.22 (.19)
Canada (French)	27	35.1 (13.9)	.30 (.47)	.54 (.21)	.78 (.42)	6.2 (1.2)	.25 (.22)
Chile	36	36.9 (12.4)	.50 (.51)	.41 (.18)	.58 (.50)	3.2 (2.1)	.31 (.20)
China	56	26.0 (4.8)	.48 (.50)	.44 (.19)	.88 (.33)	3.9 (1.5)	.49 (.14)
Denmark	35	34.6 (14.4)	.40 (.50)	.60 (.22)	.69 (.47)	5.5 (1.2)	.29 (.17)
France	51	27.3 (10.5)	.49 (.50)	.63 (.22)	.51 (.50)	5.4 (1.3)	.36 (.18)
Ghana	61	31.1 (10.4)	.54 (.50)	.52 (.25)	.49 (.50)	5.5 (1.5)	.63 (.17)
India	50	33.2 (8.3)	.40 (.49)	.49 (.26)	.38 (.49)	4.0 (2.1)	.60 (.22)
Israel (Jewish)	71	23.9 (3.1)	.51 (.50)	.58 (.22)	.86 (.35)	6.0 (1.2)	.22 (.18)
Israel (Palest.)	32	19.0 (2.1)	.59 (.50)	.44 (.21)	.94 (.25)	5.2 (1.5)	.36 (.19)
Italy	37	24.4 (6.0)	.68 (.47)	.57 (.16)	.89 (.31)	5.6 (1.3)	.24 (.15)
Japan	36	21.5 (1.7)	.44 (.50)	.53 (.25)	.89 (.32)	3.5 (1.6)	.35 (.17)
New Zealand	32	45.6 (17.8)	.44 (.50)	.63 (.27)	.69 (.47)	6.9 (.3)	.32 (.21)
Russia	32	29.9 (10.1)	.59 (.50)	.41 (.20)	.88 (.34)	3.6 (2.0)	.57 (.22)
Senegal	48	31.0 (10.1)	.33 (.48)	.51 (.16)	.35 (.48)	2.8 (1.7)	.60 (.18)
Sweden	31	44.2 (13.7)	.45 (.51)	.63 (.20)	.61 (.50)	5.6 (.9)	.32 (.23)
U.K.	48	40.8 (15.0)	.63 (.49)	.48 (.25)	.23 (.42)	6.8 (.5)	.30 (.19)
U.S.A.	184	24.6 (11.8)	.65 (.48)	.62 (.25)	.65 (.48)	6.9 (.4)	.38 (.19)

Note, these numbers pertain to the cases that are used in the analyses; some unreliable cases were dropped during the processing of the physiological data (as described above).

Table A2. Participants' Evaluations of Video Negativity by Country

	Mean Rating of Negative Stories	Mean Rating of Positive Stories	Difference
Brazil	3.94	1.15	2.79***
Canada (English)	5.17	1.46	3.71***
Canada (French)	4.03	1.51	2.52***
Chile	4.63	1.43	3.20***
China	4.47	1.23	3.25***
Denmark	4.81	1.54	3.27***
France	4.72	1.51	3.21***
Ghana	3.74	1.86	1.88***
India	3.42	1.72	1.70***
Israel (Jewish)	5.34	1.56	3.78***
Israel (Palest.)	5.09	1.76	3.33***
Italy	4.71	1.15	3.56***
Japan	4.10	1.79	2.31***
New Zealand	4.37	1.39	2.98***
Russian	4.90	1.38	3.52***
Senegal	3.88	2.28	1.61***
Sweden	4.35	1.56	2.79***
U.K.	4.40	1.76	2.64***
U.S.A.	4.53	1.41	3.12***

Note, the scale runs from 1 to 7. ***$p < .001$; **$p < .01$; *$p < .05$

Table A3. Ideology and Negativity Bias, International vs Local Videos

	International Videos	Local Videos
Individual Data		
- Effect of Ideology on GSL Difference (pooled)	.104 (.093)	-.172 (.157)
Stimulus Data		
- Effect of Ideology * Negativity Interaction on GSL (pooled)	.045 (.048)	-.078 (.068)
- Number of Samples with Significant Interaction	1 pos.	0
Time-Series Data		
- Effect of Ideology * Negativity Interaction on GSL (pooled)	.001 (.001)	-.001 (.001)
- Number of Samples with Significant Interaction	1 pos.	1 neg.

***p < .001; **p < .01; *p < .05

Table A4. Ideology and Negativity Bias, Threatening vs Disgusting Photos

	Negative vs Positive Photos	Threatening vs Positive Photos	Disgusting vs Positive Photos
Individual Data			
- Effect of Ideology on GSL Difference (pooled)	-.069*	-.074	-.053
	(.034)	(.042)	(.042)
Stimulus Data			
- Effect of Ideology * Negativity Interaction on GSL (pooled)	-.012	-.014	-.008
	(.007)	(.009)	(.008)
- Number of Samples with Significant Interaction	2 neg.	2 neg.	0
Time-Series Data			
- Effect of Ideology * Negativity Interaction on GSL (pooled)	-.002	-.003	-.002
	(.002)	(.002)	(.002)
- Number of Samples with Significant Interaction	1 pos.	1 pos.	2 pos.

***p < .001; **p < .01; *p < .05

Table A5. Ideology and Negativity Bias by Stimuli (Stimulus-Level Data)

	Effect of Ideology * Negativity Interaction on GSL (Pooled Data)	Number of Samples with Significant Interaction
Negative Videos		
- Peru Fire	-.072 (.146)	1 negative
- May Day Protest	.264 (.141)	2 positive
- Niger Shortages	.169 (.140)	1 positive
- Sri Lanka Crimes	.049 (.142)	1 positive
Threatening Photos		
- Spider	-.128 (.070)	3 neg. / 1 pos.
- War Scene	-.036 (.069)	0
- Attack	-.058 (.069)	1 neg. / 1 pos.
- Aimed Gun	-.116 (.071)	1 negative
- Knife	-.062 (.070)	1 negative
Disgusting Photos		
- Mutilation	-.013 (.071)	1 positive
- Cockroach on Food	-.066 (.070)	1 negative
- Dirty Toilet	-.054 (.070)	1 negative
- Person Vomiting	-.062 (.070)	2 positive

***$p < .001$; **$p < .01$; *$p < .05$

Table A6. Different Measures of Ideology and Negativity Bias

	Full W-P	Midpoint W-P	Median W-P	Full L-R	Median L-R	Full Combined	Median Combined
Video Experiment							
Individual Data							
- Effect of Ideology on GSL	.104	.006	.022	.100	.052	.144	.104*
Difference (pooled)	(.093)	(.044)	(.042)	(.080)	(.042)	(.102)	(.041)
Stimulus Data							
- Effect of Ideology * Negat.	.045	.002	.012	.058	.028	.075	.056**
Interaction on GSL (pooled)	(.048)	(.023)	(.022)	(.042)	(.022)	(.053)	(.022)
- Number of Samples with		1 neg.					
Significant Interaction	1 pos.	1 pos.	1 pos.	1 pos.	1 pos.	1 pos.	1 pos.
Time-Series Data							
- Effect of Ideology * Negat.	.001	.000	.001*	.000	.000	.001	.001***
Interaction on GSL (pooled)	(.001)	(.000)	(.000)	(.001)	(.000)	(.001)	(.000)
- Number of Samples with				1 neg.			
Significant Interaction	1 pos.	2 pos.	1 pos.	3 pos.	1 pos.	1 pos.	3 pos.
Photo Experiment							
Individual Data							
- Effect of Ideology on GSL	-.069*	-.037*	-.018	-.041	.013	-.074*	-.012
Difference (pooled)	(.034)	(.016)	(.015)	(.029)	(.015)	(.037)	(.015)
Stimulus Data							
- Effect of Ideology * Negat.	-.012	-.008*	-.002	-.008	.004	-.014	-.001
Interaction on GSL (pooled)	(.007)	(.003)	(.003)	(.006)	(.003)	(.008)	(.003)
- Number of Samples with							1 neg.
Significant Interaction	2 neg.	1 neg.	2 neg.	0	1 pos.	1 neg.	1 pos.
Time-Series Data							
- Effect of Ideology * Negat.	-.002	-.002*	-.001	-.001	.001	-.002	-.000
Interaction on GSL (pooled)	(.002)	(.001)	(.001)	(.001)	(.001)	(.002)	(.001)
- Number of Samples with		1 neg.					
Significant Interaction	1 pos.	1 pos.	0	2 pos.	2 pos.	2 pos.	0

***p < .001; **p < .01; *p < .05

Table A7. Ideological Items and Negativity Bias (Pooled Individual-Level Data)

	Negative vs Positive Videos	Threatening vs Positive Photos	Disgusting vs Positive Photos
Full Scale	.104	-.074	-.053
	(.093)	(.042)	(.042)
Abortion	.031	-.027	-.015
	(.049)	(.021)	(.022)
Capitalism	.008	-.005	.014
	(.052)	(.023)	(.023)
Censorship	-.055	-.070**	-.032
	(.050)	(.022)	(.022)
Death Penalty	.080	-.022	-.017
	(.047)	(.021)	(.021)
Gay Marriage	-.005	-.031	-.029
	(.049)	(.021)	(.022)
Gun Control	.033	.005	-.031
	(.063)	(.028)	(.028)
Immigration	.078	-.006	-.001
	(.053)	(.024)	(.024)
Military Spending	.000	-.029	-.012
	(.050)	(.022)	(.022)
Obedience	.005	-.019	-.015
	(.051)	(.022)	(.023)
Patriotism	.123*	-.021	.001
	(.052)	(.023)	(.023)
Pollution Control	-.019	.036	.001
	(.081)	(.035)	(.035)
Socialism	.018	.037	-.027
	(.051)	(.023)	(.023)
Tax Cuts	.014	-.051*	-.029
	(.050)	(.022)	(.022)
Women's Equality	.102	-.016	.029
	(.090)	(.038)	(.038)

***p < .001; **p < .01; *p < .05

Table A8. Ideology and Negativity Bias Among Subgroups

	All Participants	More Extreme Participants	More Interested Participants
Video Experiment			
Individual Data			
- Effect of Ideology on GSL Difference (pooled)	.104	.206	.323**
	(.093)	(.111)	(.121)
Stimulus Data			
- Effect of Ideology * Negativity Interaction on GSL (pooled)	.045	.073	.152*
	(.048)	(.055)	(.064)
- Number of Samples with Significant Interaction	1 pos.	1 pos.	0
Time-Series Data			
- Effect of Ideology * Negativity Interaction on GSL (pooled)	.001	.002*	.002**
	(.001)	(.001)	(.001)
- Number of Samples with Significant Interaction	1 pos.	1 pos.	1 pos.
Photo Experiment			
Individual Data			
- Effect of Ideology on GSL Difference (pooled)	-.069*	-.053	-.082
	(.034)	(.040)	(.045)
Stimulus Data			
- Effect of Ideology * Negativity Interaction on GSL (pooled)	-.012	-.006	-.011
	(.007)	(.008)	(.010)
- Number of Samples with Significant Interaction	2 neg.	2 neg.	1 neg.
Time-Series Data			
- Effect of Ideology * Negativity Interaction on GSL (pooled)	-.002	-.001	-.002
	(.002)	(.002)	(.002)
- Number of Samples with Significant Interaction	1 pos.	1 pos.	2 pos.

***p < .001; **p < .01; *p < .05