Online Appendix for:
Political Costs of Trade War Tariffs

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A Survey Questions and Sampling Procedures

CBS Poll (2018). The CBS poll was conducted by telephone from June 14 to June 17, 2018, among a random sample of 1,100 adults nationwide. Data collection was conducted by Social Science Research Solutions (SSRS) of Glen Mills, PA, on behalf of CBS News. Phone numbers were dialed from samples of both standard land-line and cell phones.

The poll employed a random digit dial methodology. For the landline sample, a respondent was randomly selected from all adults in the household. For the cell sample, interviews were conducted with the person who answered the phone. The data have been weighted to reflect U.S. Census figures on demographic variables.

Kaiser Family Foundation Poll (2018). The KFF poll was conducted by telephone from June 11 to June 20, 2018, among a random sample of 1,257 adults nationwide. Data collection was conducted by SSRS of Glen Mills, PA, on behalf of the Henry J. Kaiser Family Foundation. Phone numbers were dialed from samples of both standard land-line and cell phones using a Computer-Assisted Telephone Interview (CATI) technique.

The KFF poll also included an oversample of prepaid (pay-as-you-go) telephone numbers (N=235) to obtain a sample of lower-income and non-White respondents. We focus on the random sample in our analysis because our identification strategy relies on the random sampling of observations before and after the escalation of the trade war. However, as we show in Table A-10, our results are robust to including the prepaid sample.

Gallup Poll (2018). Gallup conducted a weekly survey of 1,508 U.S. adults on presidential approval, electoral preferences, and other demographics from June 11 to June 17, 2018. The Gallup poll relies on live (not automated) interviews, dual-frame sampling (which includes random-digit-dial (RDD) list-assisted landline interviewing and RDD wireless phone sampling to reach those in wireless-only and wireless-mostly households), and a random selection method for choosing respondents within the landline household. Unlike the other two polls, Gallup generally concludes the surveys between 4:00 p.m. and 10:30 p.m. CST Monday to Friday. Saturday, 10 a.m.-3 p.m. CST, and Sunday, 1 p.m.-6 p.m. CST.

Survey Questions

- CBS. Do you approve or disapprove of the way Donald Trump is handling his job as president?

  Approve

  Disapprove

(DO NOT READ) Don't know/no answer

- KFF. Do you approve or disapprove of the way Donald Trump is handling his job as President?
- GET ANSWER, THEN ASK: Do you strongly or somewhat (approve/disapprove)?

  Strongly approve
  Somewhat approve
  Somewhat disapprove
  Strongly disapprove
  (DO NOT READ) Don't know
  (DO NOT READ) Refused
- Gallup. Do you approve or disapprove of the way Donald Trump is handling his job as president?

  Approve
  Disapprove
  DK
  Refused
- GET ANSWER, THEN ASK THOSE WHO DIDN'T KNOW/REFUSED: Do you lean more towards approve or more towards disapprove?

  Approve
  Disapprove
  DK
  Refused
- CBS. Do you approve or disapprove of Donald Trump's decision to impose new tariffs on steel and aluminum imports?

  Approve
  Disapprove
  (DO NOT READ) Don't know
- CBS. Some countries have said that if the U.S. puts tariffs on steel and aluminum, they will put their own new tariffs on U.S. products, an exchange some have labeled a trade war. If there is a trade war between the U.S. and other countries, do you feel the U.S. economy would come out (better) in the long run, (worse) in the long run, or would that make no difference in the long run?

  Better
  Worse

No difference

(DO NOT READ) Don't know/No answer

- CBS. Do you feel you would be personally affected by a trade war, either through the prices you pay or the business you work for, or would you probably not be affected?
- (IF YES, AFFECTED: Would that be for the better or for the worse?)

  Affected for the better

  Affected for the worse

  Not affected

  (DO NOT READ) Don't Know/No answer
- CBS. Do you approve or disapprove of the way Donald Trump is handling the issue of immigration?

  Approve

  Disapprove

  (DO NOT READ) Don't know
- CBS. Do you approve or disapprove of the way Donald Trump is handling the situation with North Korea?

  Approve

  Disapprove

  (DO NOT READ) Don't know

Gallup. We have some questions about the election for Congress, which will be held November 6th (2018). Do you, yourself, plan to vote in the election this November or not?

Yes

No

DK

Refused

Gallup. (If the elections for Congress were being held today, which party's candidate would you vote for in your Congressional district–the Democratic Party's candidate or the Republican Party's candidate?) (If undecided, ask:) As of today, do you lean more toward the Democratic Party's candidate or the Republican Party's candidate?

Democratic candidate

Republican candidate

Other candidate

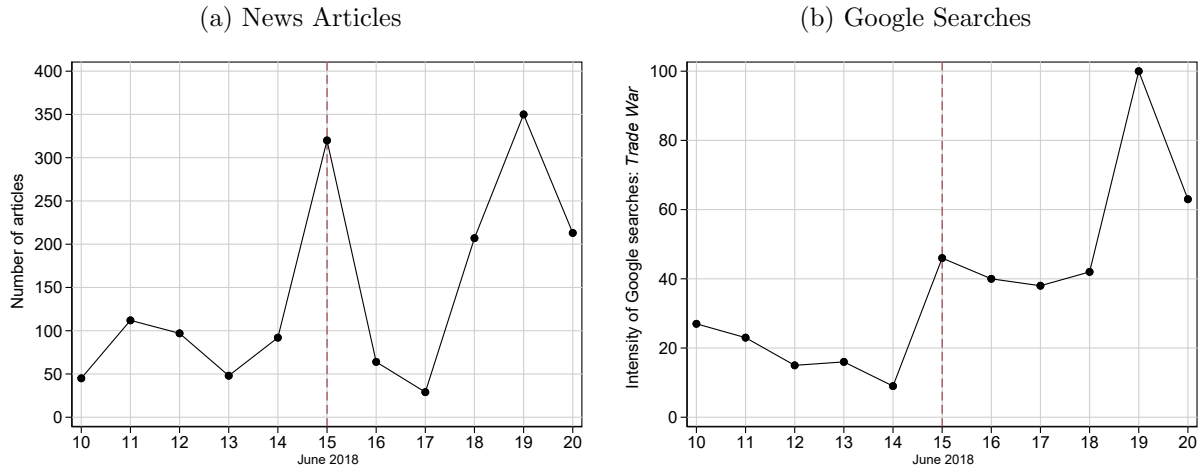
Undecided

B Media Coverage of the June 2018 Round of Tariffs

On June 15, 2018, the Trump administration released its list of Chinese products on which it planned to impose tariffs. The Chinese Ministry of Finance announced in a statement released on Friday afternoon (June 15), Eastern Standard Time—or early Saturday morning in Beijing (June 16)—that China would retaliate. Therefore, the press was unable to cover the story until the following day, on June 16. Online and television news sites started to cover China's retaliation almost immediately after the Chinese Ministry of Finance's announcement on June 15. For example, CNN announced at 2:31 PM:

> "The world's two biggest economies are now at war over trade in the week of President Trump's whopping 25 percent tariff on Chinese exports. China has just retaliated with its own tariffs against the U.S. It will also impose a 25 percent tax on $50 billion of U.S. goods."

Figure (A-1) Trade war salience over time



Note: Panel (a): News articles in the Nexis Uni database that included the keywords: tariff* and retaliat* and Chin*. Panel (b): Relative intensity of Google searches of the keywords: "trade war."

We downloaded from the Nexis Uni database all articles published by U.S.-based media outlets that matched the following keywords: tariff*, retaliat*, and Chin*. This search yielded 1,778 results. As panel (a) in Figure A-1 shows, there was a steep 247% increase in published news articles that covered the trade war tariffs. An analysis of Google trends provides a similar general trend (panel b). The intensity of Google searches of the term

"trade war" spiked on June 15, and also remained considerably higher throughout the post-escalation fieldwork period.

On June 18, Trump further escalated his trade war with China by threatening another $200 billion of tariffs if China retaliates again. Thus, the post-escalation treatment can be interpreted not as a single event to which exposure peaks immediately after the cutoff and diminishes over time, but rather as a cumulative treatment comprised of a series of "escalation events."

Overall, a closer examination of the evidence indicates that respondents interviewed on the morning or noon of June 15 were probably still unaware of the escalation in the trade war, since the media did not begin to cover this issue until later that day, whereas respondents interviewed on June 16 or later were very likely to be aware of the new tariffs. We therefore use June 16 as our benchmark cutoff date that divides respondents into control and treatment groups in both the CBS and KFF samples, where information about the exact time of each interview is unavailable. Reassuringly, however, the estimated post-escalation effects on Trump approval are substantively and statistically similar based on both surveys if we (1) use June 15 as the cutoff date or (2) exclude observations collected on June 15 (Table A-7). Unlike the other two polls, Gallup conducted the interviews between 4:00 p.m. and 10:30 p.m. and provides data on the exact time of each interview. We are therefore able to carefully assign respondents interviewed in the evening of June 15 to the treatment group.

New York Times Front Pages

To get a more vivid sense of how trade war tariffs were communicated to the public, we also reviewed the New York Times' (NYT) front pages before and after the imposition of China's retaliatory tariffs. The NYT did not mention the trade war on its June 14 or June 15 front pages, but coverage of the trade war was on its front page on both June 16 and 17.

Furthermore, those front-page articles provided specific details on the magnitude of the Chinese tariffs and the main targeted commodities ("...$50 billion worth of American goods including beef, poultry, tobacco and cars"), and an assessment of their potential economic ramifications:

> "The trade actions could ripple through the global economy, fracturing supply chains and costing jobs at American companies that will be forced to absorb higher prices. Although the United States economy is especially strong, the tariffs are expected to drive up prices for American consumers as well as for

businesses that depend on China for parts.

Things could get worse if the United States and China ratchet up their actions. Mr. Trump has already promised more tariffs in response to China's retaliation. China, in turn, is likely to back away from an agreement to buy $70 billion worth of American agricultural and energy products..."

To the extent that the NYT captures the most salient daily news reported by a wide variety of media outlets, this suggests that respondents interviewed on June 16 and later were more likely to be aware of the trade war escalation compared to those interviewed earlier. Nevertheless, our analysis in Tables A-7 and A-8 shows that the anti-incumbent effect remains statistically significant and substantively large whether we define June 15 or June 16 as the cutoff that divides respondents into the control and treatment groups.

C Balance and Robustness Tests

Table (A-1) Balance Test

	Control (N=541)		Treated (N=504)	
	Mean	Std. Dev.	Mean	Std. Dev.
Female	0.48	0.50	0.47	0.50
Age	54.3	18.4	54.3	18.3
High school or less	0.31	0.46	0.31	0.46
Some college	0.24	0.43	0.25	0.43
College graduate	0.44	0.50	0.44	0.50
Income (6 categories)	4.00	1.62	3.99	1.62
Republican	0.42	0.49	0.43	0.50
Democrat	0.48	0.50	0.47	0.50
Independent	0.10	0.30	0.10	0.30
Non-Hispanic white	0.70	0.46	0.70	0.46
Non-Hispanic black	0.13	0.33	0.10	0.30
Hispanic	0.07	0.25	0.11	0.31
Other ethnicity	0.10	0.30	0.09	0.29
City	0.26	0.44	0.26	0.44
Suburbs	0.47	0.50	0.48	0.50
Town/Rural/other	0.26	0.44	0.25	0.44

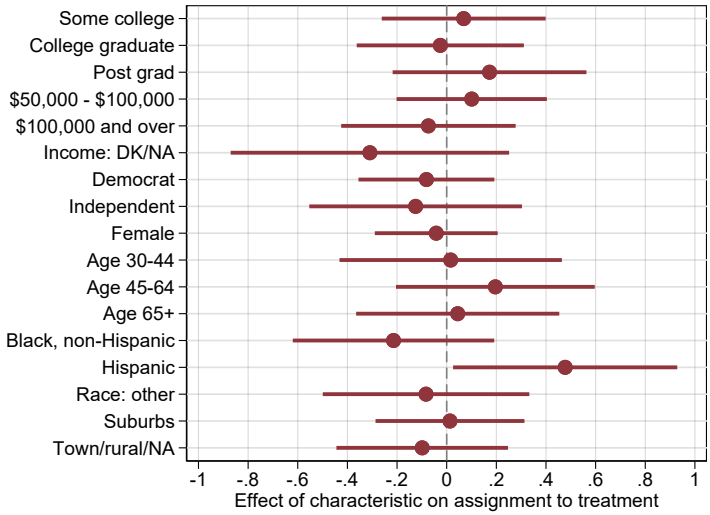
Note: Respondent characteristics by exposure to the post-escalation treatment.

In Table A-1, we show that the CBS sample used in our primary analysis (Table 1) is well-balanced and the observable characteristics of control and treated respondents are similar. In figure A-2, we use a logistic regression to predict assignment into the treatment group by respondent characteristics. We find that the minor differences between control and treatment respondents are not statistically significant across all characteristics except one: Hispanic ethnicity.

A potential concern arising from this minor imbalance is that the slightly larger share of Hispanic respondents in the treatment group is the reason for the lower level of Trump approval in the treatment group. If that were the case, then we should have seen no anti-incumbent effect when we restrict the sample to non-Hispanic respondents only, or when we re-weight the sample using entropy balancing to adjust for unbalanced covariate distributions (Hainmueller, 2012). However, Table A-2 shows that the anti-incumbent effect remains significant and sizable in both cases.

By reweighting the sample units, entropy balancing ensures that treated and nontreated groups of observations are similar in terms of their observed characteristics. Here, this means that individuals interviewed after the trade war escalation and those who were interviewed before that are, on average, similar across a wide range of variables, including ethnicity, when using the reweighted sample—as we show in Table A-3.

Figure (A-2) Effect of respondent characteristics on assignment to treatment



Note: Markers are logistic regression estimates with 95% confidence intervals. The dependent variable is a binary indicator of assignment to treatment (i.e., it is equal to 1 if the date of interview is June 16 or later.)

Table (A-2) Post-escalation treatment effect among non-Hispanic respondents and in the reweighted sample

	(1) Trump Approval	(2) Trump Approval
Post-escalation	-0.070**	-0.045*
	(0.024)	(0.022)
Covariates	✓	✓
State FE	✓	✓
Test	No Hispanic Rs	Entropy balancing
Observations	989	1082
Pseudo R-squared	0.532	0.534

Note: Column 1 restricts the sample to non-Hispanic respondents. Column 2 uses entropy balancing to adjust for unbalanced covariate distributions.

Table (A-3) Balance over exposure to the post-escalation treatment before and after using entropy balancing

	Treated			Control		
(a) Before entropy balancing	mean	variance	skewness	mean	variance	skewness
Some college	0.246	0.186	1.179	0.238	0.182	1.229
College graduate	0.258	0.192	1.108	0.277	0.200	0.998
Post grad	0.194	0.157	1.546	0.177	0.146	1.694
$50,000 - $100,000	0.344	0.226	0.656	0.313	0.216	0.804
$100,000 and over	0.250	0.188	1.155	0.252	0.189	1.141
Income: DK/NA	0.046	0.044	4.326	0.072	0.067	3.317
Democrat	0.465	0.249	0.139	0.476	0.250	0.095
Independent	0.098	0.089	2.703	0.109	0.097	2.516
Female	0.471	0.250	0.116	0.483	0.250	0.067
Age 30-44	0.173	0.143	1.728	0.177	0.146	1.694
Age 45-64	0.385	0.237	0.474	0.343	0.226	0.660
Age 65+	0.319	0.218	0.776	0.338	0.224	0.685
Black, non-Hispanic	0.098	0.089	2.703	0.126	0.110	2.253
Hispanic	0.108	0.096	2.531	0.070	0.065	3.369
Race: other	0.092	0.084	2.817	0.105	0.094	2.576
Suburbs	0.485	0.250	0.062	0.469	0.249	0.123
Town/rural/NA	0.254	0.190	1.131	0.271	0.198	1.028

(b) After entropy balancing	mean	variance	skewness	mean	variance	skewness
Some college	0.246	0.186	1.179	0.246	0.186	1.179
College graduate	0.258	0.192	1.108	0.258	0.192	1.108
Post grad	0.194	0.157	1.546	0.194	0.157	1.546
$50,000 - $100,000	0.344	0.226	0.656	0.344	0.226	0.656
$100,000 and over	0.250	0.188	1.155	0.250	0.188	1.155
Income: DK/NA	0.046	0.044	4.326	0.046	0.044	4.321
Democrat	0.465	0.249	0.139	0.465	0.249	0.139
Independent	0.098	0.089	2.703	0.098	0.089	2.702
Female	0.471	0.250	0.116	0.471	0.250	0.115
Age 30-44	0.173	0.143	1.728	0.173	0.143	1.728
Age 45-64	0.385	0.237	0.474	0.385	0.237	0.475
Age 65+	0.319	0.218	0.776	0.319	0.218	0.775
Black, non-Hispanic	0.098	0.089	2.703	0.098	0.089	2.702
Hispanic	0.108	0.096	2.531	0.108	0.096	2.532
Race: other	0.092	0.084	2.817	0.092	0.084	2.816
Suburbs	0.485	0.250	0.062	0.485	0.250	0.062
Town/rural/NA	0.254	0.190	1.131	0.254	0.190	1.131

Note: Panel (a) compares the characteristics of respondents who were randomly sampled after the trade war escalation and their non-treated counterparts. Panel (b) presents balance across the same covariates after reweighting the sample using entropy balancing.

In Table A-4, we use the pooled sample that includes both the CBS and KFF surveys. Column 1 first shows that the anti-incumbent effect remains statistically significant and sizable without including covariates in the model specification. If self-reported party affiliation is also affected by the trade war's escalation, including this variable would probably produce post-treatment bias (Montgomery, Nyhan, and Torres, 2018). However, our results are not sensitive to the inclusion of this potentially post-treatment variable. If anything, including party affiliation and other covariates somewhat reduces the magnitude of the post-escalation effect (column 2). In column 3, we use entropy balancing with the pooled sample. Column 4 also uses the reweighted, pooled sample and adds state fixed effects.

Table (A-4) Post-escalation treatment effect in the pooled and reweighted samples

	(1)	(2)	(3)	(4)
Post-escalation	-0.059**	-0.043**	-0.043**	-0.039*
	(0.022)	(0.015)	(0.015)	(0.016)
Covariates		✓	✓	✓
Reweighted sample			✓	✓
State FE				✓
Observations	2147	2147	2147	2147
R-squared	0.003	0.497	0.495	0.511

Note: Column 1 replicates the main treatment effect using the pooled sample that includes both the CBS and KFF surveys. Columns 2-3 use entropy balancing to adjust for unbalanced covariate distributions. All models control for respondents' age, gender, level of education, income, race-ethnicity, and party identification. Entries are LPM coefficient estimates with heteroskedasticity-robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

In Table A-6, we use data on respondents' county of residence which are not available in the CBS sample, to examine the robustness of our findings to any minor imbalances in county-level exposure to the retaliatory tariffs (see Table A-5) and to standard error clustering by county.

As Table A-5 shows, and as expected by the random digit dial sampling, the sample is well balanced over exposure to tariffs. The average respondent in the control (treatment) group resides in a county in which 1.6 (1.7) percent of all workers are targeted by the Chinese tariffs. Similarly, 24 (27) percent of the respondents interviewed before (after) the trade war escalation reside in a targeted county (i.e., a county in the top-quartile of the distribution).

Column 1 in Table A-6 replicates the main treatment effect using the full KFF sample (i.e., including the prepaid sample) and controlling for the extent to which respondents' county of residence was directly targeted by the Chinese tariffs. Column 2 uses the random sample only. In Column 3, we use entropy balancing to adjust for unbalanced covariate distributions, including any minor imbalances in county-level exposure to the retaliatory

Table (A-5) Exposure to Chinese tariffs across the post-escalation treatment, KFF sample

a. Targeted by Chinese tariffs by June 2018 (%)	Mean	SE	Median	Min	Max
Control (pre-escalation)	1.65	0.13	0.43	0	34.9
Treated (post-escalation)	1.72	0.19	0.43	0	48.8
b. Targeted by Chinese tariffs by June 2018 (top quartile)					
Control (pre-escalation)	0.24	0.02	0	0	1
Treated (post-escalation)	0.27	0.02	0	0	1

Note: Panel (a) uses the variable *exposure to Chinese tariffs*, which is the share of workers employed in industries directly targeted by Chinese retaliatory tariffs by June 2018 in each county. Panel (b) uses a dummy variable that equals 1 for counties located in the top quartile of the distribution of *exposure to Chinese tariffs*.

tariffs by China by June 2018. As expected due to the random sampling and the very minor imbalances presented in Table A-5, the results hold across all these statistical tests. Furthermore, in columns 4-5, we show that effect remains statistically significant using both heteroskedasticity-robust standard errors and standard errors clustered by county of residence.

Table (A-6) Post-escalation treatment effect, (reweighted) KFF sample

	(1)	(2)	(3)	(4)	(5)
Post-escalation	-0.049*	-0.056*	-0.047*	-0.047*	-0.047*
	(0.022)	(0.023)	(0.021)	(0.022)	(0.024)
Targeted by Chinese tariffs (std)	0.016	0.001	0.023	0.023	0.023
	(0.018)	(0.020)	(0.016)	(0.021)	(0.021)
Covariates	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Sample	full	random	reweighted	reweighted	reweighted
Standard Errors	OLS	OLS	OLS	robust	clustered
Observations	1434	1207	1207	1207	1207
R-squared	0.466	0.496	0.505	0.505	0.505

Note: All models control for respondents' age, gender, level of education, income, race-ethnicity, party identification, and type of local community. Entries are LPM coefficient estimates with standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

In Table 1, we use June 16 as the cutoff date that divides respondents into control and treatment groups. This means that respondents interviewed on June 15 are coded as control units. As we mentioned above, China's formal retaliation was announced and covered by the media only in the afternoon of June 15, which means that many of the interviewees that day were still unexposed to the treatment. Nevertheless, we show below that the results remain intact when we code respondents interviewed on June 15 as treated units or when we exclude them from the analysis.

In the main text, we treat Don't Know (DK) responses as a neutral stance on Trump approval, and code them as 0 in our main dependent variable. Below, we show that our

Table (A-7) Post-escalation treatment effect by cutoff selection, CBS Poll

	(1) Trump Approval	(2) Trump Approval	(3) Trump Approval
Post-escalation (June 15)	-0.053*		
	(0.025)		
Post-escalation (June 16)		-0.068*	-0.060**
		(0.027)	(0.023)
Covariates	✓	✓	✓
State FE	✓	✓	✓
June 15 coded as:	treated	missing	control
Observations	1082	824	1082
R-squared	0.502	0.536	0.503

Note: CBS Poll. Fieldwork period: June 14-17. Entries are linear probability model estimates with standard errors in parentheses. All models control for respondents' age, gender, level of education, income, race/ethnicity, party affiliation, and type of locality. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table (A-8) Post-escalation treatment effect by cutoff selection, KFF Poll

	(1) Trump Approval	(2) Trump Approval	(3) Trump Approval
Post-escalation (June 15)	-0.051*		
	(0.023)		
Post-escalation (June 16)		-0.052*	-0.048*
		(0.023)	(0.023)
Covariates	✓	✓	✓
State FE	✓	✓	✓
June 15 coded as:	treated	missing	control
Observations	1211	1188	1211
R-squared	0.508	0.512	0.508

Note: KFF Poll. Fieldwork period: June 11-21. Entries are linear probability model estimates with standard errors in parentheses. All models control for respondents' age, gender, level of education, employment status, income, race/ethnicity, party affiliation, and type of locality. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

results remain substantively similar across both surveys when we (1) exclude DK responses; (2) code DK responses as the midpoint.

In Table 1, we use linear probability models (LPM) to estimate the effect of the trade war. In Table A-11, we show that the results are similar when we use logistic regression instead.

Table (A-9) Treatment Effect and Coding "Don't Know" Responses, CBS Poll

	(1) Approve (0/1)	(2) Approve (0/1)	(3) Approve (1-3)
Post-escalation	-0.065**	-0.039+	-0.098*
	(0.023)	(0.022)	(0.043)
Covariates	✓	✓	✓
State FE	✓	✓	✓
DK coded as	0	missing	midpoint (2)
Observations	1082	1028	1082
R-squared	0.495	0.566	0.538

Note: CBS Poll. DK=Don't Know. Entries are LPM/OLS estimates with standard errors in parentheses. All models control for respondents' age, gender, level of education, race/ethnicity, and party affiliation. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table (A-10) Treatment Effect and Coding "Don't Know" Responses, KFF Poll

	(1) Approve (0/1)	(2) Approve (0/1)	(3) Approve (0/1)	(4) Approve (1-4)	(5) Approve (1-5)
Post-escalation	-0.043*	-0.050*	-0.057*	-0.167**	-0.227**
	(0.022)	(0.023)	(0.023)	(0.057)	(0.076)
Covariates	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
DK coded as	0	0	missing	missing	midpoint (3)
Sample	full	random	random	random	random
Observations	1439	1211	1165	1165	1196
R-squared	0.473	0.504	0.541	0.578	0.568

Note: KFF Poll. DK=Don't Know. Entries are LPM/OLS estimates with standard errors in parentheses. All models control for respondents' age, gender, level of education, race/ethnicity, employment status and party affiliation. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table (A-11) Effects of Trade War Escalation on Voter Positions, Logistic Regression

	(1) Trump Approval	(2) Approves U.S. Tariffs on Steel	(3) Worse off: U.S. economy	(4) Worse off: Respondent	(5) Placebo: Immigration Policy	(6) Placebo: North Korea
Post-escalation	-0.426*	-0.302+	0.317*	0.165	-0.102	-0.031
	(0.192)	(0.162)	(0.158)	(0.145)	(0.190)	(0.172)
Covariates	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	1075	1076	1076	1076	1068	1070
Pseudo R-squared	0.471	0.294	0.274	0.170	0.458	0.368

Note: Entries are logistic model estimates with standard errors in parentheses. All models control for respondents' age, gender, level of education, race/ethnicity, and party affiliation. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

In Table 2, we show the anti-incumbent effect heterogeneity across respondent characteristics using OLS. Below, we show that the results hold when we use ordered probit models instead. The variable "In the labor force" is a binary indicator for either employed respondents or unemployed respondents who are seeking employment (0=unemployed and not seeking employment, student, retired, homemaker, or on disability). High-income is a binary indicator for income categories above the annual median income in the sample, i.e., at least $75,000. Targeted by Chinese tariffs is a dummy for respondents living in counties in the top quartile of the distribution of the share of employment being targeted by Chinese tariffs by June.

Table (A-12) Effect Heterogeneity, ordered probit estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Trump approval						
Post-escalation	-0.254**	-0.322**	-0.398**	-0.320**	-0.266**	-0.124
	(0.085)	(0.102)	(0.140)	(0.105)	(0.098)	(0.111)
Post-escalation X College graduate		0.209				
		(0.176)				
Post-escalation X In the labor force			0.227			
			(0.175)			
Post-escalation X High-income				0.184		
				(0.174)		
Post-escalation X Targeted by Chinese tariffs					0.043	
					(0.187)	
Post-escalation X Republican						-0.306+
						(0.168)
Covariates	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	1076	1076	1076	1076	1076	1076
Pseudo R-squared	0.784	0.784	0.784	0.784	0.784	0.784

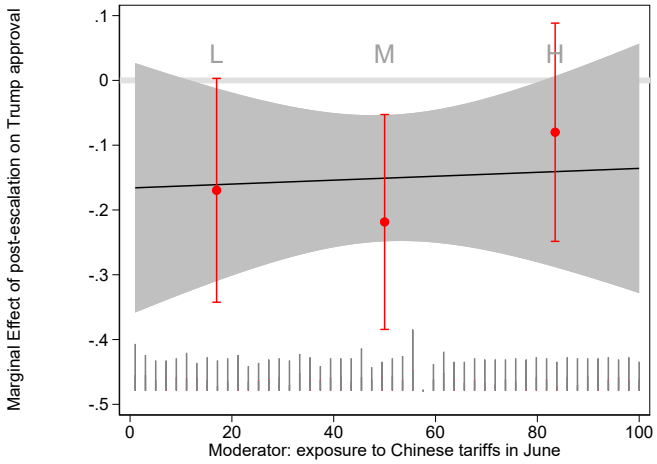
Note: The dependent variable is a 4-point scale of Trump approval. Entries are oridnal probit coefficient estimates with standard errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

In Table 2, we show that the post-escalation effect does not significantly vary across county-level exposure to Chinese tariffs. The variable we use to measure a high-level of exposure to retaliatory tariffs is an indicator for respondents living in counties at the top quartile of the distribution of being targeted by Chinese tariffs by June 2018 (i.e., including April). Below, we show that the results hold using (1) percentile ranks; (2) measuring exposure to tariffs imposed only in June; or (3) measuring exposure to tariffs imposed by other countries in addition to China.

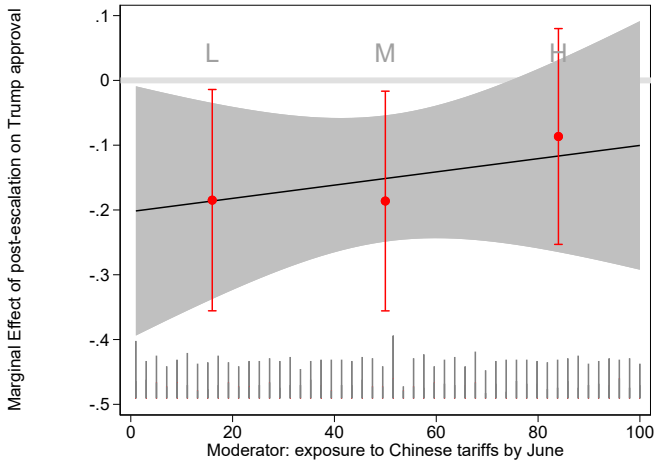
Figure A-3 shows that the marginal post-escalation effect on Trump's approval rating is similar across the distribution of county-level exposure to retaliatory tariffs. Each of the three moderators measures exposure to retaliatory tariffs first by calculating the share of workers employed in industries directly targeted by retaliatory tariffs and then using the percentile rank of these variables.

Figure (A-3) Post-escalation effect by county-level exposure to tariffs

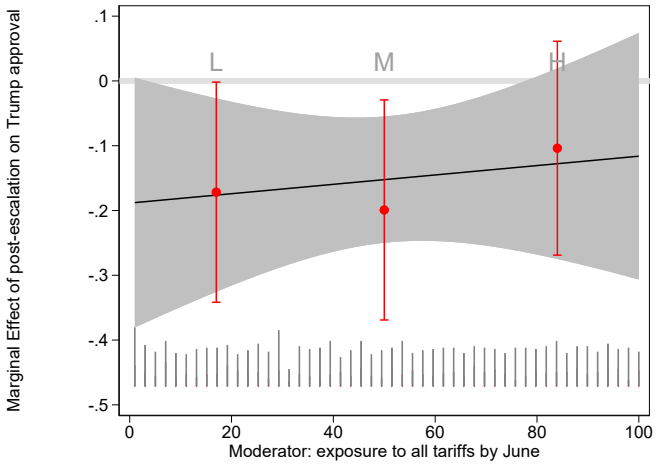
(a) Chinese tariffs, June



(b) Chinese tariffs, by June



(c) All tariffs, by June



Note: Marginal effect of the post-escalation treatment by exposure to: panel (a): Chinese tariffs imposed in June; panel (b): Chinese tariffs imposed by June (i.e., including the April round of tariffs); and, panel (c): all tariffs (i.e., by China, Mexico, Canada, and the EU) imposed by June.

In all three cases, the anti-Trump effect is statistically similar across the distribution of exposure to retaliatory tariffs. If anything, the effect is somewhat more noticeable in the low and middle parts of the distribution, which is at odds with the notion that personal- or local-level material considerations drive the post-escalation decrease in Trump's approval rating. Instead, these results indicate that voters punished the incumbent regardless of the extent to which they were directly targeted by retaliatory tariffs.

In Table 3, we show that the trade war's escalation affected voting preferences. Our empirical strategy relies on the random sampling of survey respondents around the trade war's escalation on June 15, 2018. In our benchmark model specification, we control for respondents' demographic and socioeconomic characteristics, party identification, reachability (the number of call attempts—1, 2, 3, or at least 4—until completing the interview, and phone status: cell only, cell and landline, or landline only), and state fixed effects. Below, we show that our results are robust to a range of tests, including using entropy balancing, employing a linear probability model instead of a logistic regression model, and using various model specifications.

Table (A-13) Balance over exposure to the post-escalation treatment before and after using entropy balancing, Gallup

		Treated			Control	
(a) Before entropy balancing	mean	variance	skewness	mean	variance	skewness
Age 35-54	0.296	0.209	0.896	0.278	0.201	0.989
Age 55+	0.502	0.250	-0.007	0.514	0.250	-0.056
Female	0.469	0.249	0.124	0.485	0.250	0.061
Non-Hispanic Black	0.108	0.097	2.522	0.111	0.098	2.484
Hispanic	0.101	0.091	2.641	0.120	0.106	2.341
Race: other	0.055	0.052	3.905	0.057	0.054	3.811
Some college	0.325	0.220	0.749	0.296	0.209	0.896
College graduate	0.467	0.249	0.131	0.470	0.249	0.120
$24,000-$48,000	0.180	0.148	1.662	0.192	0.155	1.566
$48,000-$90,000	0.278	0.201	0.989	0.252	0.189	1.144
$90,000-$120,000	0.122	0.107	2.310	0.124	0.109	2.284
$120,000 and over	0.203	0.162	1.479	0.209	0.166	1.431
Income: DK/REF	0.098	0.088	2.705	0.126	0.111	2.247
% Targeted by Chinese tariffs	1.523	9.824	4.844	1.420	9.492	5.230
Democrat	0.486	0.250	0.055	0.465	0.249	0.141
(b) After entropy balancing	mean	variance	skewness	mean	variance	skewness
Age 35-54	0.296	0.209	0.896	0.295	0.208	0.897
Age 55+	0.502	0.250	-0.007	0.502	0.250	-0.007
Female	0.469	0.249	0.124	0.469	0.249	0.124
Non-Hispanic Black	0.108	0.097	2.522	0.108	0.097	2.521
Hispanic	0.101	0.091	2.641	0.102	0.091	2.639
Race: other	0.055	0.052	3.905	0.055	0.052	3.904
Some college	0.325	0.220	0.749	0.325	0.220	0.749
College graduate	0.467	0.249	0.131	0.467	0.249	0.131
$24,000-$48,000	0.180	0.148	1.662	0.180	0.148	1.662
$48,000-$90,000	0.278	0.201	0.989	0.278	0.201	0.990
$90,000-$120,000	0.122	0.107	2.310	0.122	0.107	2.310
$120,000 and over	0.203	0.162	1.479	0.203	0.162	1.479
Income: DK/REF	0.098	0.088	2.705	0.098	0.089	2.701
% Targeted by Chinese tariffs	1.523	9.824	4.844	1.523	9.821	4.684
Democrat	0.486	0.250	0.055	0.486	0.250	0.056

Note: Using the Gallup sample, Panel (a) compares the characteristics of respondents who were randomly sampled after the trade war escalation and their non-treated counterparts. Panel (b) presents balance across the same covariates after reweighting the sample using entropy balancing.

In Panel (a) of Table A-13, we show that the Gallup sample is well-balanced and the

observable characteristics of control and treated respondents are similar. In Panel (b), we use entropy balancing to rewieght the sample units and ensure that treated and nontreated respondents are identical in terms of their observed characteristics.

Using the reweighted Gallup sample, Table A-14 shows that our results remain statistically similar. The magnitude of the post-escalation effects is smaller but remains sizable, with an estimated decrease of 3.5 percentage points in voters' support for Republican candidates and a 4-points increase in their support for Democratic candidates.

Table (A-14) Post-escalation effect on voting preferences, reweighted Gallup sample

	(1) Trump Approval	(2) Vote Republican	(3) Vote Democrat	(4) Won't Vote
Post-escalation	-0.053**	-0.034*	0.042**	-0.003
	(0.020)	(0.017)	(0.014)	(0.019)
Covariates	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	1333	1333	1333	1333
R-squared	0.534	0.649	0.763	0.160

Note: Entries are LPM coefficient estimates with heteroskedasticity-robust standard errors in parentheses, using the reweighted Gallup sample. All models control for the covariates presented in Table A-13. * $p < 0.05$, ** $p < 0.01$.

In our main analysis, we consider party identification to be an important pre-treatment covariate. But controlling for partisanship might produce post-treatment bias if self-reported party affiliation is also affected by the trade war's escalation. However, as Table A-15 shows, our results also hold when we do not control for partisanship.

Table (A-15) Post-escalation effect on voting preferences without controlling for party identification

	(1) Trump Approval	(2) Vote Republican	(3) Vote Democrat	(4) Won't Vote
Post-escalation	-0.487**	-0.364**	0.407**	0.011
	(0.129)	(0.129)	(0.128)	(0.176)
% Targeted by Chinese tariffs	0.067*	0.039	-0.040	-0.027
	(0.028)	(0.026)	(0.027)	(0.041)
Covariates	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	1333	1333	1333	1333
Pseudo R-squared	0.139	0.135	0.128	0.175

Note: Gallup. Entries are logistic regression estimates with standard errors in parentheses. All models control for respondents' age, gender, ethnicity, level of education, income, and county-level exposure to Chinese tariffs. * $p < 0.05$, ** $p < 0.01$.

The results also remain statistically and substantively similar without controlling for neither demographic and socioeconomic characteristics nor respondents' reachability (number of call attempts and phone status), when we regress the dependent variables on the post-escalation treatment controlling for state fixed effects only (Table A-16).

Table (A-16) Post-escalation effect on voting preferences without controlling for demographics, socioeconomic characteristics, and reachability

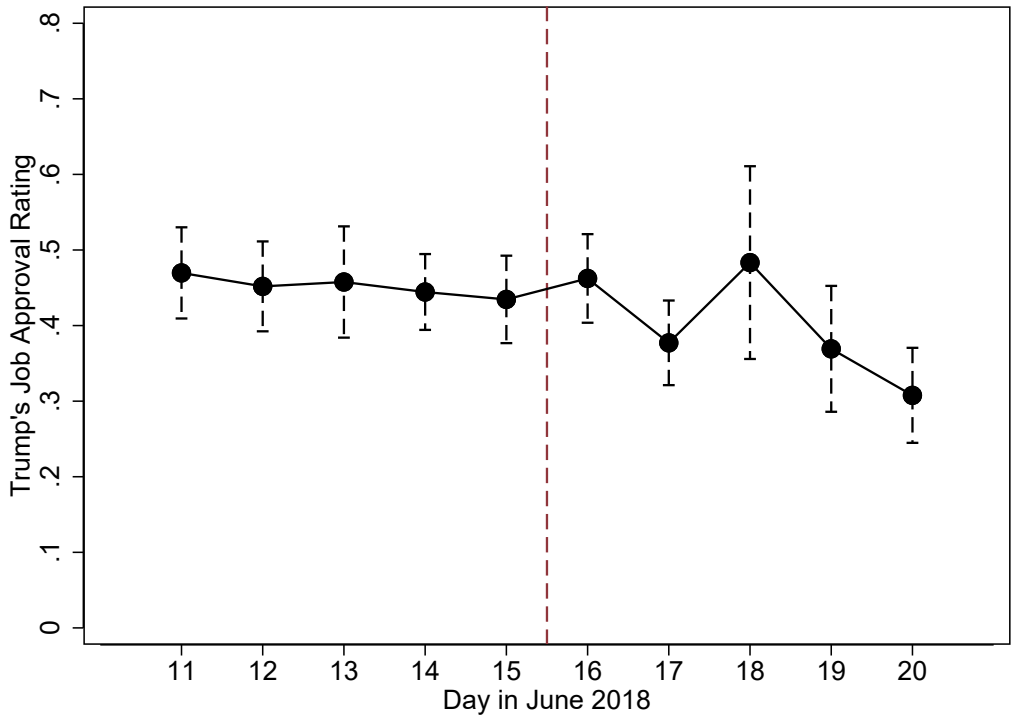
	(1) Trump Approval	(2) Vote Republican	(3) Vote Democrat	(4) Won't Vote
Post-escalation	-0.314**	-0.246*	0.293*	-0.077
	(0.116)	(0.116)	(0.115)	(0.154)
State FE	✓	✓	✓	✓
Observations	1333	1333	1333	1333
Pseudo R-squared	0.049	0.043	0.038	0.033

Note: Gallup. Entries are logistic regression estimates with standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

D Additional Results

In Figure A-4, we show Donald Trump's daily approval rate. The analysis shows that the Trump's job approval rating was fairly stable in the pre-escalation period. Following the imposition of tariffs by the Trump administration and China, Trump's approval rates are significantly lower in three out of the five days of the post-escalation period available in our data.

Figure (A-4) Donald Trump's job approval rating by day



Note: Markers are daily approval rates in the pooled sample with 95% confidence intervals.

Table A-17 shows the full tabular results of the analysis in Table 2.

Table (A-17) Effect Heterogeneity, full tabular results

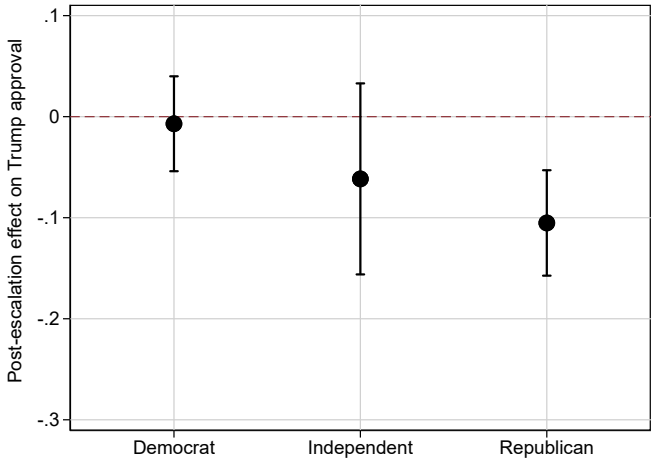
	(1)	(2)	(3)	(4)	(5)	(6)
Post-escalation	-0.169**	-0.225**	-0.289**	-0.224**	-0.183*	-0.069
	(0.062)	(0.076)	(0.101)	(0.078)	(0.071)	(0.078)
Post-escalation X College graduate		0.163				
		(0.128)				
Post-escalation X In the labor force			0.189			
			(0.127)			
Post-escalation X High-income				0.147		
				(0.127)		
Post-escalation X Targeted by Chinese tariffs					0.053	
					(0.138)	
Post-escalation X Republican						-0.260*
						(0.125)
College graduate	-0.294**	-0.353**	-0.295**	-0.289**	-0.294**	-0.298**
	(0.067)	(0.081)	(0.067)	(0.067)	(0.067)	(0.067)
In labor force	0.099	0.098	0.029	0.102	0.097	0.094
	(0.074)	(0.074)	(0.087)	(0.074)	(0.074)	(0.074)
Above median income	-0.085	-0.078	-0.082	-0.138+	-0.084	-0.088
	(0.066)	(0.066)	(0.066)	(0.080)	(0.066)	(0.066)
Targeted by Chinese tariffs	0.115	0.116	0.108	0.115	0.095	0.114
	(0.070)	(0.070)	(0.071)	(0.070)	(0.088)	(0.070)
Republican	1.652**	1.658**	1.658**	1.658**	1.651**	1.744**
	(0.062)	(0.063)	(0.062)	(0.063)	(0.062)	(0.076)
Black, non-Hispanic	-0.374**	-0.366**	-0.376**	-0.372**	-0.373**	-0.365**
	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)
Hispanic	-0.068	-0.063	-0.069	-0.064	-0.069	-0.066
	(0.095)	(0.096)	(0.095)	(0.095)	(0.095)	(0.095)
Other/RF	0.106	0.108	0.103	0.100	0.105	0.109
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
Age 25-34	0.139	0.134	0.134	0.137	0.139	0.136
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
Age 35-44	0.150	0.145	0.142	0.143	0.150	0.160
	(0.108)	(0.109)	(0.109)	(0.109)	(0.109)	(0.108)
Age 45-54	0.369**	0.363**	0.364**	0.365**	0.367**	0.359**
	(0.111)	(0.111)	(0.111)	(0.111)	(0.112)	(0.111)
55-64	0.124	0.121	0.120	0.123	0.123	0.113
	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)
65+	0.301**	0.294**	0.291**	0.298**	0.300**	0.303**
	(0.111)	(0.112)	(0.112)	(0.111)	(0.112)	(0.111)
Female	-0.210**	-0.207**	-0.210**	-0.207**	-0.211**	-0.209**
	(0.059)	(0.059)	(0.058)	(0.059)	(0.059)	(0.058)
Covariates	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	1076	1076	1076	1076	1076	1076
R-squared	0.521	0.522	0.522	0.522	0.521	0.523

Note: The dependent variable is a 4-point scale of Trump approval. Entries are OLS coefficient estimates with standard errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

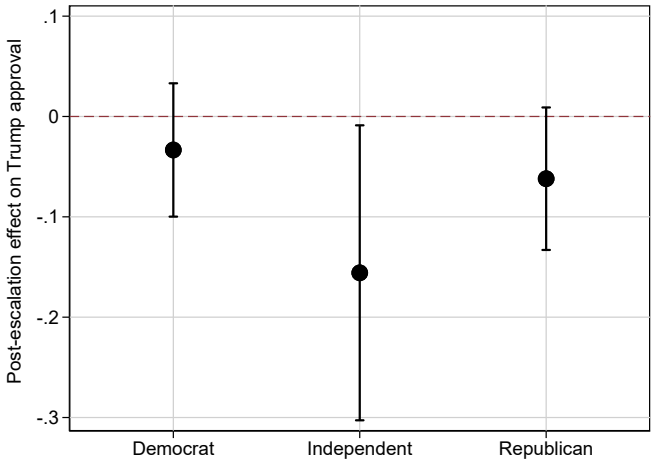
In Figure A-5, we show the marginal effect of the post-escalation treatment by partisan affiliation using the pooled sample, the CBS sample, and the KFF sample. The analysis shows that the anti-incumbent effect is mainly concentrated among Republican and Independent voters, and very small and statistically non-significant among Democrats.

Figure (A-5) Post-escalation effect by party affiliation and sample

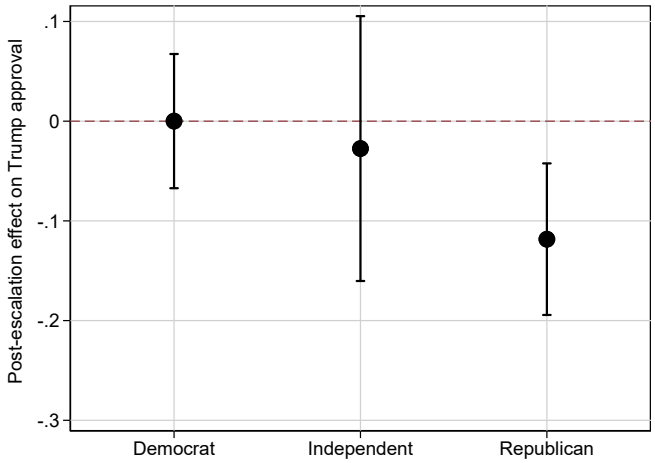
(a) Pooled sample



(b) CBS sample



(c) KFF sample



E Cooperative Congressional Election Survey 2018

Our main results focus on the immediate effects of the escalation in the U.S.-China trade war on support for Trump and his protectionist policies. Here, we examine the extent to which the public's reaction to the conflicts were lasting and electorally consequential. To address this issue, we examine whether the mass attitudes about the trade war in the fall of 2018 influenced (1) Trump's approval rating at that time and (2) voting in the 2018 U.S. midterm elections. Our analysis draws on the 2018 Cooperative Congressional Election Survey (CCES), a large-scale study capable of capturing variation across a wide variety of legislative constituencies. The CCES was conducted in two waves: a pre-election wave that was in the field from September to November and a post-election wave that was in the field from November to December. In the former wave, respondents were asked whether they approved of how Trump was doing his job. In the latter wave, they were asked whether and, if so, for whom they voted.

We focus on three binary dependent variables: whether respondents (1) approved of the way Trump was performing prior to the election, (2) voted for the Republican candidate for the House of Representatives, and (3) decided not to cast a ballot. We regress each of these variables on respondents' views on imposing tariffs against China, which was assessed by asking "On the issue of trade, do you support or oppose $50 billion worth of tariffs on goods imported from China?" All of the following LPMs control for a wide range of factors, including respondents' age, gender, ethnicity, level of education, family income decile, party identification, employment status, industry of employment, type of locality, and either state or county fixed effects. We also control for exposure to the local economic impact of China's retaliatory tariffs, using a standardized measure of the share of workers per county who are employed in industries targeted by those tariffs. Since we are interested in the extent to which opposition to the trade war changed voting behavior, we limit our sample to respondents who reported that they voted for Trump in the 2016 presidential election.

The analysis yields a number of notable findings. First, among Trump voters, opposition to tariffs against China was associated with a substantial (15-16 percentage point) reduction in approval of Trump in the run-up to the election (columns 1-2). Second, this sizable and significant relationship exists even after controlling for respondents' sector of employment and the extent to which their community was targeted by China's retaliatory tariffs. Again, these findings suggest that the disapproval of Trump stemming from the trade war was an outgrowth of national, rather than personal or local, considerations. Third, opposition to Trump's tariffs is negatively correlated with voting for the Republican candidate in House

Table (A-18) Opposition to U.S. tariffs on Chinese imports and electoral outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Trump Approval		Voted GOP		Didn't vote	
Opposes tariffs against China	-0.162**	-0.151**	-0.086**	-0.081**	0.009	0.010
	(0.013)	(0.014)	(0.016)	(0.015)	(0.006)	(0.007)
Targeted by China's tariffs	0.003		-0.007		0.002	
	(0.003)		(0.005)		(0.002)	
Covariates	✓	✓	✓	✓	✓	✓
State FE	✓		✓		✓	
County FE		✓		✓		✓
Observations	10145	10145	10145	10145	10352	11198
R-squared	0.171	0.317	0.257	0.444	0.058	0.290

Note: Entries are logistic coefficient estimates with standard errors clustered by state in parentheses. All models control for respondents' age, gender, ethnicity, level of education, local exposure to Chinese tariffs by June, and state of residence. At the county level, we control for change in the Republican vote share between the 2014 and 2016 House elections, and include a dummy variable for swing districts. * $p < 0.05$, ** $p < 0.01$.

elections (columns 3-4). This 8-9 point effect is both politically and statistically significant.

Finally, the available evidence suggests that opposition to the trade war affected the elections by reducing support for Republican candidates, rather than by depressing turnout, since such opposition was not associated with whether respondents went to the polls (columns 5-6).

Table (A-19) Opposition to U.S. tariffs on Chinese imports and electoral outcomes, full sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Trump Approval		Voted GOP		Didn't vote	
Opposes tariffs against China	-0.239**	-0.235**	-0.139**	-0.136**	-0.003	-0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.002)	(0.003)
Targeted by China's tariffs	0.003		-0.001		0.000	
	(0.003)		(0.004)		(0.001)	
Covariates	✓	✓	✓	✓	✓	✓
State FE	✓		✓		✓	
County FE		✓		✓		✓
Observations	28278	28278	28278	28278	28196	30035
R-squared	0.716	0.740	0.682	0.721	0.022	0.142

Note: CCES 2018. Full sample. Entries are linear probability model estimates with standard errors in parentheses. All models control for respondents' age, gender, ethnicity, level of education, family income decile, party affiliation, employment status, industry of employment, and type of locality (big city/suburbs/small town/rural area). At the county level, we control for change in the Republican vote share between the 2014 and 2016 House elections, and a dummy for swing districts. The variable *Targeted by China's tariffs* is a standardized measure of the share of workers in a county working in industries targeted by China's import tariffs. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

In Table A-19, we show that the results are substantively and statistically similar when we use the full sample (i.e., including voters who did not vote for Trump in 2016).

In Table A-20, we show that the results are also similar for the Senate elections: oppo-

Table (A-20) Opposition to U.S. tariffs on Chinese imports and electoral outcomes, Senate Elections

	(1)	(2)	(3)	(4)
	Senate Elections			
	Voted GOP		Didn't vote	
Opposes tariffs against China	-0.111**	-0.095**	0.004	0.003
	(0.017)	(0.016)	(0.009)	(0.010)
Targeted by China's tariffs	0.002		0.001	
	(0.005)		(0.002)	
Covariates	✓	✓	✓	✓
State FE	✓		✓	
County FE		✓		✓
Observations	7468	7468	8060	8432
R-squared	0.557	0.654	0.214	0.284

Note: The sample is restricted to respondents who reported they have voted for Trump in 2016. Entries are LPM estimates identical to those in Table A-18, except that the dependent variables are: voted for the Republican candidate/ didn't vote in the Senate elections (instead of the House elections). + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

sition to Trump's tariffs among his base is associated with a lower probability of voting for the Republican candidate in the Senate elections.

The results show that opposition to Trump's tariffs is negatively associated with voting for a Republican candidate in the midterm elections. We interpret this association as representing at least to some extent the anti-incumbent effect of discontentment with Trump's trade policy. However, an important concern regarding this analysis is that this effect might represent a spurious correlation that stems from some sort of reverse causality (where disapproval of Trump and the Republican party more generally also determines opposition to tariffs more specifically). To be sure, the limitations of our cross-sectional data do not allow us to fully address this potential source of bias. However, below we show that our results hold controlling for various potential confounders, including (pre-election) approval of Trump, ideology, or attitudes toward specific issue areas other than trade. The robustness of our findings is not consistent with the proposition that the effect we find is merely an artifact of respondents' broader ideology or approval of president Trump.

In Table A-21, we show that the results remain statistically significant when we control for respondents' (pre-election) approval of Trump. The magnitude of the effect of opposition to tariffs is considerably smaller after controlling for Trump approval more broadly, but it is still far from negligible (4.4 percentage points).

In Table A-22, we control for respondents' ideological position, the perceived ideology of Trump, and the perceived ideological gap between the respondent and president Trump. Ideological position is measured using a 7-point scale from "very liberal" to "very conserva-

Table (A-21) Opposition to U.S. tariffs on Chinese imports and voting for Republican Candidates, controlling for Trump approval

	(1)	(2)
Opposes tariffs against China	-0.086**	-0.044**
	(0.016)	(0.014)
Targeted by China's tariffs	-0.007	-0.008
	(0.005)	(0.005)
Trump approval		0.258**
		(0.027)
Covariates	✓	✓
State FE	✓	✓
Observations	10145	10145
R-squared	0.257	0.286

Note: The sample is restricted to respondents who reported they have voted for Trump in 2016. Entries are LPM estimates with robust standard errors in parentheses clustered by county. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

tive." Ideological gap ranges from -6 (those who perceive Trump as very liberal and locate themselves as very conservative) to 6 (those who perceive Trump as very conservative and self-identify as very liberal). The effect of opposition to tariffs against China remains statistically and substantively similar controlling for respondents' perceptions about the broader ideology of themselves and the incumbent president.

Table (A-22) Opposition to U.S. tariffs on Chinese imports and voting for Republican Candidates, controlling for ideology

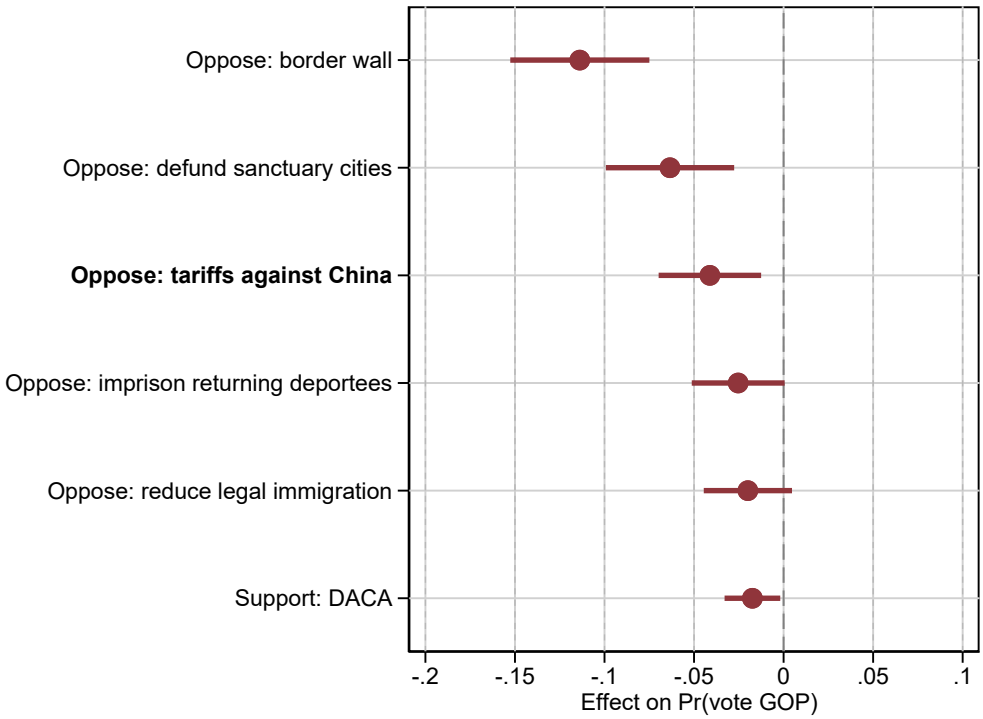
	(1)	(2)	(3)	(4)
Opposes tariffs against China	-0.076**	-0.067**	-0.067**	-0.075**
	(0.015)	(0.015)	(0.015)	(0.015)
Targeted by China's tariffs	-0.007	-0.008	-0.008	-0.007
	(0.005)	(0.005)	(0.005)	(0.005)
Ideological placement: respondent		0.034**	0.034**	
		(0.005)	(0.005)	
Ideological placement: Trump			-0.002	
			(0.004)	
Trump-respondent ideological gap				-0.015**
				(0.004)
Covariates	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	9759	9759	9759	9759
R-squared	0.253	0.265	0.265	0.257

Note: The sample is restricted to respondents who reported they have voted for Trump in 2016. Entries are LPM estimates with robust standard errors in parentheses clustered by county. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

In Figure A-6, we add five variables measuring attitudes toward different aspects of immigration policy to our benchmark model presented in Table A-18, column 1. The Figure

shows first that the effect of opposition to tariffs remains statistically significant even after controlling for respondents' positions on immigration policy, including policies that are most clearly associated with Trump, such as border security and the expansion of the Mexico–United States border barrier. Second, the magnitude of the effect estimate of opposition to tariffs is weaker than two of the five immigration coefficients, but larger than three of them (and statistically distinguishable only from the effect estimate of opposition to the border wall). On the one hand, these results are in line with previous studies suggesting that trade is a low-salience electoral issue compared to other issues, including immigration (Guisinger, 2009). On the other hand, the magnitude of the effect of opposition to tariffs is not negligible (4.1 points) even after controlling for immigration attitudes, which is consistent with the proposition that the U.S.-China trade war has made trade a more salient electoral issue compared to previous years (Lake and Nie, 2022).

Figure (A-6) The association between opposition to Trump's tariffs and vote choice compared to immigration items



Note: Markers are LPM point estimates with 95% confidence intervals.)

In Figure A-7, we conduct a principal component analysis (PCA) for six issue areas available in the CCES 2018 survey: trade, immigration, taxes, health care, abortion, and gun control. For each of the six sets of survey items described below, we construct a summary scale that combines the different survey items by extracting the first component of a PCA. As Table A-23 shows, the first component explains a large share of the total variance across all six principal component analyses.

Table (A-23) Principal Component Analysis

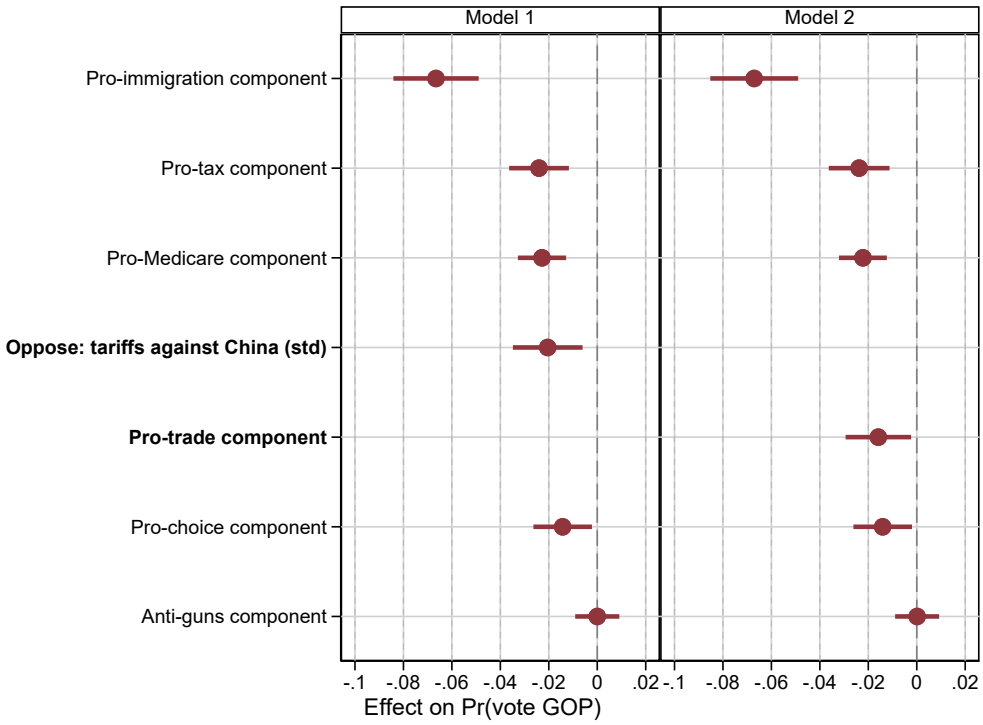
k	Trade Components	Taxes Components	Guns control Components	Health-care Components	Immigration Components	Abortion Components
1	0.61	0.53	0.58	0.45	0.59	0.50
2	0.25	0.29	0.24	0.28	0.15	0.17
3	0.15	0.18	0.17	0.14	0.11	0.11

Note: Proportion explained by the first three components of the principal component analysis.

The left-panel in Figure A-7 reports the results of two linear probability models adding

to the benchmark specification (Table A-18, column 1) the new measures extracted by the PCA. The model also standardizes all five summary measures and the indicator of opposition to U.S. tariffs against China to have a mean of zero and a standard deviation of one. Model 2 in the same Figure only replaces the China-specific measure with the PCA-based summary measure for trade attitudes.

Figure (A-7) The association between opposition to Trump's tariffs and vote choice compared to other issue areas



Note: Markers are LPM point estimates with 95% confidence intervals.)

First, the association between trade preferences and voting for the Republican candidate remains statistically significant even after controlling for respondents' attitudes toward five additional issue areas, several of which are arguably among the most contentious issues in American politics. Second, attitudes toward immigration are most strongly associated with respondents' vote choice in the 2018 midterm election by a wide margin. A one standard deviation increase on the pro-immigration summary scale is associated with a 6 percentage points decrease in voting for the Republican candidate. Third, the analysis indicates that, controlling for all other factors, respondents' vote choice was not correlated with their attitudes toward gun control. Finally, the association between trade preferences and voting for

the Republican candidate is of similar magnitude to the effects of respondents' preferences on taxes, abortion, and health-care: A one standard deviation increase on each of these summary scales is associated with a decrease of approximately 2 percentage points in voting for the Republican candidate.

The following six sets of variables are used to build the six scales (response categories are either support/for or oppose/against in all cases):

Pro-Trade summary measure.

- Withdraw the United States from the Trans-Pacific Partnership trade agreement, a free trade agreement that included the U.S., Japan, Australia, Vietnam, Canada, Chile, others.
- On the issue of trade, do you support or oppose the following proposed tariffs - $50 billion worth of tariffs on goods imported from China
- On the issue of trade, do you support or oppose the following proposed tariffs - 25% tariffs on imported steel and 10% on imported aluminum, EXCEPT from Canada, Europe and Mexico.

Pro-Immigration summary measure.

- Increase spending on border security by $25 billion, including building a wall between the U.S. and Mexico.
- Provide legal status to children of immigrants who are already in the United States and were brought to the United States by their parents. Provide these children the option of citizenship in 10 years if they meet citizenship requirements and commit no crimes. (DACA).
- Reduce legal immigration by eliminating the visa lottery and ending family-based migration.
- Withhold federal funds from any local police department that does not report to the federal government anyone they identify as an illegal immigrant.
- Send to prison any person who has been deported from the United States and reenters the United States.

Pro-Taxes summary measure.

- Cut the Corporate Income Tax rate from 39 percent to 21 percent.
- Reduce the income tax rate for households earning less than $500,000 by 3 percent.
- Reduce the income tax rate for households earning more than $500,000 by 3 percent (from 40%to 37%).

Health Care summary measure (Pro-Medicare).

- Provide Medicare for all Americans.
- Repeal the entire Affordable Care Act.
- Repeal only the part of the Affordable Care Act that requires that most individuals have health insurance and that larger employers cover their employees.
- Partially repeal the Affordable Care Act. This would (1) repeal individual and employer mandates, (2) cut Medicaid payments by 25 percent, and (3) reduce taxes on expensive health plans, known as Cadillac health plans.

Abortion summary measure (Pro-Choice).

- Always allow a woman to obtain an abortion as a matter of choice.
- Permit abortion ONLY in case of rape, incest or when the woman's life is in danger.
- Ban abortions after the 20th week of pregnancy.
- Allow employers to decline coverage of abortions in insurance plans.
- Prohibit the expenditure of funds authorized or appropriated by federal law for any abortion.
- Make abortions illegal in all circumstances.

Pro-Gun Control summary measure.

- Background checks for all sales, including at gun shows and over the Internet.
- Ban assault rifles.
- Make it easier for people to obtain a concealed-carry gun permit.

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