Appendix

A Facebook vs Non-Facebook Sampling

A.1 Outreach via Web Scraping Emails

We employed several different strategies to recruit companies to obtain a diverse and representative sample of managers. We found some methods, particularly targeted Facebook ads, to be far more effective than others. As discussed in our pre-registration, our initial sampling strategy involved collecting a substantial number of email addresses of a cross-section of U.S. firms. We were interested in hearing from all firms and not just the larger publicly-traded companies with established government relations practices. To do so, we began with a random sample of all U.S. firms in the Orbis database, and then used web crawling techniques to identify email addresses. Orbis data reflects the pattern of business establishment in the U.S., meaning that the vast majority of firms represented are small (under 5 employees) and concentrated in the services sector (ex. retail, professional services, transportation, leisure and hospitality etc). This sample is appropriate because firms of all sizes and all along the supply chain, including non-tradable firms, could potentially experience tariffs if they use any tradable input. For example, housing construction is non-tradable but the steel, aluminum, and lumber used are exposed to tariffs.

However, we found this sampling method to be impractical because of aggressive spam filters and the deluge of questionable emails that business managers receive. For this initial wave during June 2019, we reached out to over 12,000 firms by email and only received 2 survey responses or 0.017 percent. Many of the emails generated by web crawling were general inquiry info@companyname.com rather than personal email addresses. After sending out a reminder email and receiving more angry requests to stop spamming respondents than actual survey responses, we changed our outreach strategy.

A.2 Outreach via Phone and Email

From August 2019 to March 2020, we assigned research assistants to manually look up the emails and phone numbers of managers, introduce the survey, and KU and BYU who worked off of the Orbis sample to call businesses during their regular business hours. Students were also given a script to ask the first ten questions of the survey over the phone rather but we still needed to follow up by sending the survey instrument by email to give the treatment.

The teams manually checked a total of 6149 firms from the Orbis sample and found a total of 3447 phone numbers. 1516 calls were made using these phone numbers and the response rate was 56 percent, the other 44 percent of numbers were either disconnected or went to an automated phone system. We judge that the phone-call-collected manager emails are likely the most reliable and up-to-date, and given that they also assented to taking a survey, those emails were given highest priority. However, many employees and managers refused to participate and the team was only able to obtain 120 valid emails. These phone conversations yielded 46 partial or complete responses. The completion rate is significantly higher than web scraping emails but still pretty low at 0.75 percent. The onset of the pandemic and the high costs of this approach led us to adjust strategy yet again with two parallel efforts.

A.3 Outreach via Purchased Emails

In June 2020, we contracted the services of FrescoData, a marketing company. They promised to email their proprietary list of 25,000 managers three times for $4000. We asked them to split the sample into control and treatment. The company estimated successful delivery rate to be 97 percent, the open rate was estimated to be 24-29 percent, and the click rate was supposed to be 6-9 percent. We expected 1500 or so responses overall but only recorded 2 partial responses, a 0.008 completion rate.

A.4 Outreach via the Kansas City Chamber of Commerce

In January 2020, we negotiated a partnership with the Kansas City Chamber of Commerce and the locally affiliated World Trade Center. The Chamber has over 2200 members in the greater Kansas City metro area, spread across 14 counties in MO and KS. 90 percent of Chamber members are defined as small businesses with fewer than 250 full time employees. But the Chamber also includes some bigger multinational companies with thousands of employees like Hallmark, H&R Block, Garmin, Cerner, and Commerce Bank as well as subsidiaries of Fortune 500 companies such as FedEx, Honeywell, PNC Bank, T-Mobile (Sprint), and Bayer (Crop Sciences). The local WTC is the international arm of the Kansas City Chamber and the local chapter of the World Trade Centers Association. Its mission is to help local businesses engage in global commerce. The Chamber agreed to help us market the survey to its members in exchange for Dr. Zhang presenting the preliminary results of our survey at the Go Global KC 2020 event and for the purchase of 10 Go Global KC tickets to raffle off as prizes. Between May and June of 2020, the Chamber advertised the survey in its newsletter and on its Facebook page. We also tasked a team of University of Kansas students and WTC interns to draft personalized messages to 570 subscribers to the WTC international trade mailing list, firms we believe are the most likely to be exposed to tariffs. These waves of outreach yielded 66 valid responses, a 3 percent completion rate.

An example is below:

Subject: **U.S.-China Trade War Survey**

Dear Ms. Dunn,

We hope you, your family, and your team are staying safe and healthy during this time. We understand that the COVID-19 pandemic poses unprecedented challenges for many industries and may be having an impact on TVH as well.

The World Trade Center [redacted] is partnering with the [redacted] to survey greater [redacted] area businesses about their experience with the U.S.-China trade war. If you complete the survey, you will be entered for the chance to win tickets to Go Global [redacted], the premier international business event in [redacted]20 tickets available) & the [redacted] Luncheon, a one of a kind event bringing the business community and the [redacted]s players, coaches and staff together to kick off the season (2 tickets available).

[redacted] is a group of researchers investigating the impact of rising tariffs on U.S. businesses. They have developed a web application, the Tariff Impact Report, that helps estimate the cost of new tariffs for companies and industries around the country. They are a non-profit, academic research group, and will provide you access to a Tariff Impact Report customized for your business free of charge.

To access your company's report and for a chance to win tickets, all we ask is that a manager first fill-out a short 10-minute survey about your business' experience with the trade war (whether positive, negative, or neutral). The survey is available from this link:

https://[redacted].az1.qualtrics.com/jfe/form/SV_0iHpHx8rlEMjvmJ

All data collected in this survey are confidential, which means we will not publish or share data with anyone that could identify your company or its personnel.

The collective findings of the survey in the [redacted] area will be presented during the WTC's signature event, *Go Global* [redacted] on August 11th.

We look forward to your insights and hope to connect with more business leaders in the [redacted] Area. If you have any questions regarding this study, please contact [redacted] collaborator, at [redacted]

Sincerely,

KAITLIN BAST
Manager

WORLD TRADE CENTER®
[redacted]

[redacted] **Chamber of Commerce**
[redacted]

Figure A1: Sample Personalized Email from Chamber

A.5 Outreach via Targeted Facebook Ads

Targeted ads on Facebook proved to be our most effective sampling strategy. During 2019, we also experimented with contacting managers through Twitter or LinkedIn but found Facebook to be the most cost-effective. We paid to target ads at managers in the United States. We ran two rounds of targets ads on Facebook in June 2019 and July 2020.

We over-incentivized the first round of sampling by offering a $5 gift Amazon card. A large number of participants lied about being a manager in order to obtain the reward. We describe below the methods we used to cull the 1747 responses obtained from this wave down to 603 valid responses. We also ran a second round of ads without any incentives one year later, after the Phase One Trade Deal was signed and the onset of the COVID-19 pandemic exacerbated supply chain issues. This wave yielded 335 valid responses. It is hard to calculate a comparable completion rate for the Facebook sample. But we calculate it to be 938 responses from 100,000? impressions. This is a comparably low completion rate as the validated email outreach but much more cost effective.

A.6 Validation of Facebook Sample

Research assistants at the University of Kansas and Wesleyan University helped devise a system for detecting suspicious responses from the Facebook sample based on total response time, IP addresses, and verifying the business name or manager email. The criteria for whether or not a response was invalid are as follows (need two hits to be deemed invalid):

1) *Total response time* - Flagged responses under 120s as having a high probability of professional survey taker. Some justification for this: the non-Facebook sample had a median response time of 375s, the invalid Facebook responses had a median of 188s. Removing these the Facebook sample has a median response time of 261 seconds.

2) *googling the business name or follow up email* - Our RAs were extremely thorough. For instance, their notes include: - Followed up by e-mail and she is a part-time cannabis trimmer - Blogger. in her words "I am not a professional nail artist or anything, it's just a hobby." - Facebook page is clearly one baking student - Domain name is porn - Reposts where to answer surveys for cash

3) *Identifying duplicate or suspicious IP addresses* - Many of the multiple IP hits came from Brazil, Mexico, Venezuela, Australia, these are flagged as invalid

After applying this screening process, we ended up with 603 valid responses. Invalid: 576 responses - flagged for two or more reasons Maybe: 568 responses - unable to verify information, usually because no email was provided OR not employed at a business (ex. School, church, non-profit) Valid: 603 responses - basically anyone who is real and not trying to scam us: includes not manger, includes many one person "businesses"

The median response time for the valid Facebook sample is 261 seconds compared to 375 seconds for the non-Facebook sample (Email, Phone, Chamber). The median size of the valid Facebook sample is 8 employees, the mean is 3160. The median size of the non-Facebook sample is 7 employees, and the mean is 7539. The median tariff impact (hurt_trade) of the valid Facebook sample is 5 (neither), the mean is 4.45 (somewhat harmed). The median tariff impact of the non-Facebook sample is 4 (somewhat harmed), the mean is 3.85. This is very promising and suggests that the two are comparable for external validity purposes.

B Treatment and Outcome Texts

All respondents, both treatment and control, received the following text:

> Please read the following information about the trade war and your company, and then scroll to proceed with the survey. The imposition of tariffs in 2018, recent studies show, cost U.S. consumers and companies $1.4 billion

> a month and will force companies to redirect $165 billion per year worth of imports affected by tariffs. Furthermore, $121 billion of companies' exports to foreign markets have been harmed by retaliatory tariffs posed by other countries.

We included this information in control to ensure that the treatments were not just priming respondents about the trade war.

Respondents in the static treatment also received the following text:

> "We've crunched some numbers for you. Using data from the Bureau of Economic Analysis, we have identified the most tariff-affected industries that provide important inputs to companies in your industry."

Firms in the dynamic treatment condition were instead provided with credentials to access the web application. The invitation read:

> "We have developed an online application to allow you to calculate precisely how much extra your firm may have paid for goods and services as a result of the tariffs. The application is available exclusively to you because of your participation in our study. You can access the application here."

To measure our outcomes, we tell our respondents "Here's what you can do to [support/oppose] tariffs. Select any that you are interested in and we will share more detailed information with you on the next page." The list of actions appears in Table A1. We phrase options generally, using phrases such as "Donate to Congresspeople who oppose/support tariffs," when measuring interest, and wait until the next page to provide details (e.g. specific legislators) that could influence them. Doing so also allows us to compare this measure across opponents and supporters. We were unable to find a write-in campaign in support of the trade war or governors who publicly supported the trade war, so these action items are missing for tariff supporters.

Table A1: Outcome measures

Interest	Action (oppose)	Action (support)
Invite someone to participate in this study	Provides their e-mail address	Provides their e-mail address
Ask your Congressperson to [o] the trade war	Clicks link to Americans for Free Trade (write-in campaign)	N/A
Donate to governors who [o/s] tariffs	Clicks link to donate to a governor	N/A
Sign a petition [o/s] the trade war	Clicks link to sign petition "Republicans Fighting Tariffs"	Clicks link to sign petition from American companies seeking protection
Donate to Congresspeople who [o/s] tariffs	Clinks link to donate to sponsors of Import Tax Relief Act	Clicks link to donate to sponsors of Fair Trade with China Enforcement Act
Join Facebook groups [o/s] the trade war	Likes "Tariffs Hurt the Heartland"	Likes "American Jobs Build America"

Finally, we measure whether the individual actually takes the suggested action. We do so by tracking whether they click the provided link. While they may fail to donate or sign after clicking the link, at minimum, clicking the link represents the cost of the individual's (uncompensated) time.

C Calculating Industry-Specific Costs of Tariffs

Our goal was to estimate the costs of the trade war for a highly specific industry.

We began by creating an index of all the unique industries we wanted to generate estimates for. In the original version of our project, our sample was to be a random sample of all firms in Orbis. Even though we ended up pivoting to a primarily Facebook sample, the random sample from Orbis provided the original index of industries we estimated tariff costs for. Our Orbis sample was so large that we caught most industries using this approach. Only about 10% of our Facebook sample provided an industry for which we were missing estimates.

The Use Table (Supply-Use Framework), 2012
[Millions of dollars]
Bureau of Economic Analysis

Code	Commodity Description	Oilseed farming	Grain farming	Vegetable and melon farming	Fruit and tree nut farming	Greenhouse, nursery, and floriculture production
	Commodities/Industries	1111A0	1111B0	111200	111300	111400
1111A0	Oilseed farming	2,507	145	4		
1111B0	Grain farming		7,731			
111200	Vegetable and melon farming			909	8	
111300	Fruit and tree nut farming				189	
111400	Greenhouse, nursery, and floriculture production					3,970
111900	Other crop farming	458	223			0
112120	Dairy cattle and milk production					
1121A0	Beef cattle ranching and farming, including feedlots and dual-purpose ranching and farming	38	225	4	24	12
112300	Poultry and egg production	10				
112A00	Animal production, except cattle and poultry and eggs	24	134	2	11	6
113000	Forestry and logging					
114000	Fishing, hunting and trapping					
115000	Support activities for agriculture and forestry	2,554	9,807	1,173	2,724	767
211000	Oil and gas extraction					
212100	Coal mining					
212230	Copper, nickel, lead, and zinc mining					
2122A0	Iron, gold, silver, and other metal ore mining					
212310	Stone mining and quarrying	74	449	31	21	18
2123A0	Other nonmetallic mineral mining and quarrying	1	1,163	1	4	
213111	Drilling oil and gas wells					
21311A	Other support activities for mining					
221100	Electric power generation, transmission, and distribution	154	160	115	168	37

Figure A2: BEA Use Table

Next, we wished to identify the input industries to each industry represented in the Orbis data. To do this, we turned to the Bureau of Economic Analysis Input-Output Use Table from 2012.[52] (As of 2019, 2012 was the most recently available year for a widespread group of industries.) The Use tables provide, for every industry, the quantity that industry uses from other industries (see Figure A2).

We merged the NAICS codes from Orbis and the NAICS codes from the BEA at the 3-digit level. This resulted in matches for 94% of the industries from the Orbis data. When we merged at the 6-digit level, we found matches for only 17% of the industries from the Orbis data. We recognize that a NAICS 3-digit level will include many types of firms often facing different kinds of tariffs. However, it is more important to us to be able to match each participant to an industry code, even if it is less precise. The lack of precision may somewhat impact the quality of the information participants receive but does not interfere with our ability to estimate the causal effect of information on

[52] Available at https://www.bea.gov/industry/input-output-accounts-data.

	commodity	naics
29	1,207,990,000	111120
30	1,207,400,000	111120
31	1,207,600,000	111120
32	1,207,910,000	111120
33	1,206,000,030	111120
34	1,207,100,000	111120
35	1,204,000,000	111120
36	1,205,000,000	111120
37	1,206,000,050	111120
38	713,101,000	111130
39	713,501,000	111130
40	713,334,040	111130
41	713,394,030	111130
42	713,401,000	111130
43	713,392,010	111130
44	713,394,050	111130
45	713,201,000	111130
46	713,905,000	111130
47	713,102,000	111130
48	713,906,000	111130
49	713,392,030	111130
50	713,901,000	111130
51	713,391,000	111130
52	713,394,060	111130
53	713,322,000	111130
54	713,331,000	111130

Figure A3: Concordance from Pierce and Schott (2009)

participants' actions, which is the primary goal of our study. Since we merged at the 3-digit level, we aggregated the quantities from input industries as reported in the BEA for each 3-digit industry.

Once we knew which input industries each industry relied on, we wanted to know which commodities were associated with each input industry. We did this using a concordance from Pierce and Schott (2009).[53] The concordance identifies for each industry (6-digit NAICS) the various commodities associated with that industry (HTS codes) (see Figure A3. We aggregate industries to the 3-digit level to merge with our previous data.

Last, we wanted to know whether each commodity associated with an input industry was subject to a tariff. We used data made available by Chad Bown at the Peterson Institute for International Economics.[54] An example appears in Figure A4. The data indicate which of the various tariff lists each commodity appears on (1) or does not appear on (0).

These data allowed us to estimate, for each input industry, how many commodities it

[53] Available at http://faculty.som.yale.edu/peterschott/sub_international.htm.
[54] Available at https://piie.com/system/files/documents/bown2019-02-14.zip.

	hs10	year	init232Steel
977	7217901000	2017	1
978	7217905030	2017	1
979	7217905060	2017	1
980	7217905090	2017	1
981	7218100000	2017	1
982	7218910015	2017	1
983	7218910030	2017	1
984	7218910060	2017	1
985	7218990015	2017	1
986	7218990030	2017	1
987	7218990045	2017	1
988	7218990060	2017	1
989	7218990090	2017	1
990	7219110030	2017	1
991	7219110060	2017	1
992	7219120002	2017	1
993	7219120006	2017	1
994	7219120021	2017	1
995	7219120026	2017	1
996	7219120051	2017	1
997	7219120056	2017	1
998	7219120066	2017	1
999	7219120071	2017	1
1000	7219120081	2017	1
1001	7219130002	2017	1
1002	7219130031	2017	1

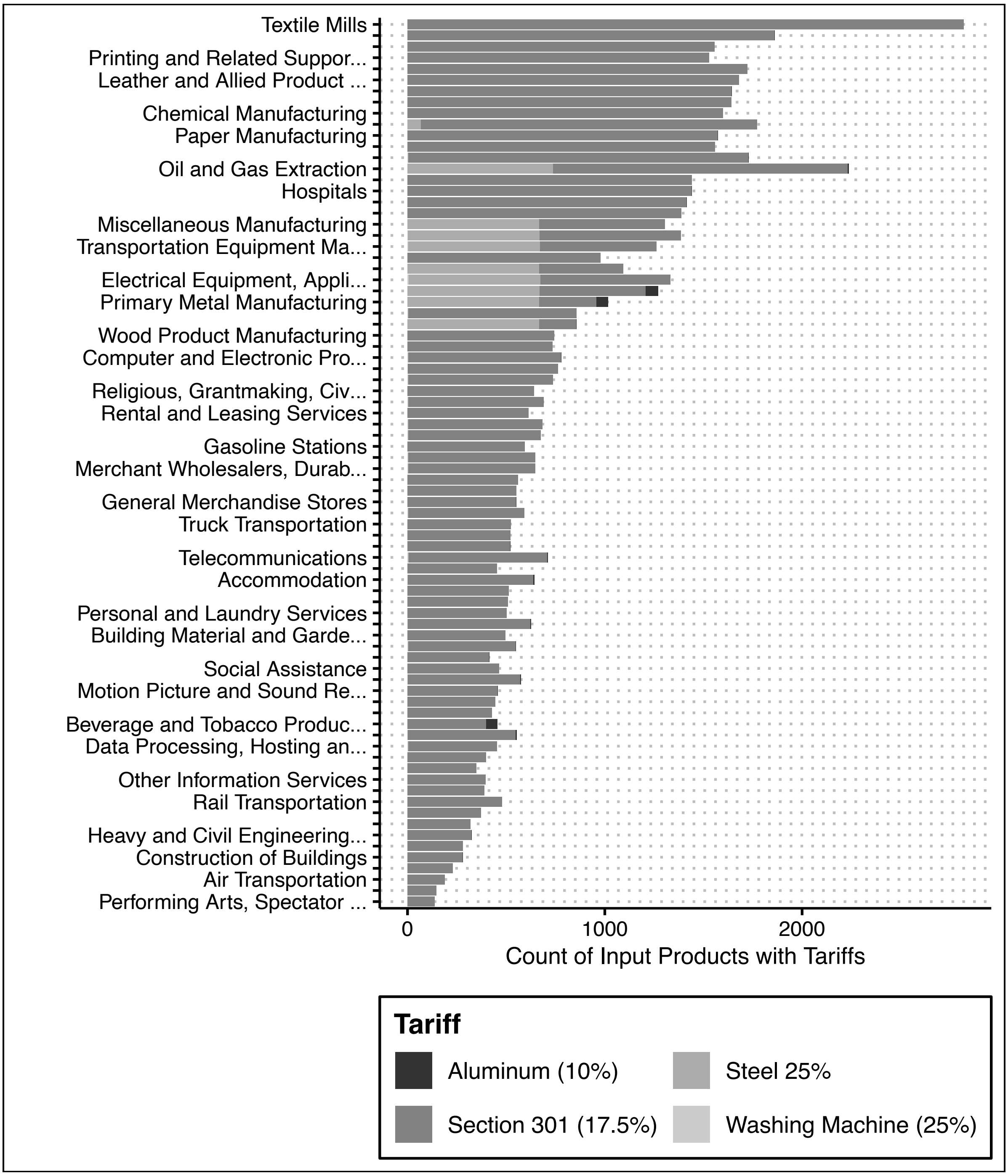
Figure A4: Tariff Lists from Bown and Zhang (2019)

was associated with, how many of those commodities appeared on tariff lists, and the average tariff rate of the lists its commodities appear on. As we explain in the main paper, we summarize this to respondents as the number of tariffed products, the proportion of tariffed products, and the average tariff rate.

We report the distribution of these costs for all industries in Figure ??. For instance, the most heavily affected industries were in manufacturing and textiles, while the least heavily affected industries were in transportation and services. (For descriptive statistics on which industries are represented in our sample, see Table 1 in the main text.)

We did not want to overwhelm respondents with information, and we did want to provide them with information that would encourage them to act to oppose the trade war. For these reasons, we chose to share with respondents the estimates for the input industries that had the highest proportion of tariffed products (Figure ??). We ordered them first according the highest proportion of tariffed products and second according to which input industries were of greatest value to the industry in question.

Figure A5: Count of Input Products with Tariffs from Trade War by NAICS 3-digit Code



The plot shows the total number of input products derived from BEA input-output tables for 3-digit NAICS code industries that had at least one tariff from the trade actions associated with the Trump trade war. Some 3-digit code names are not shown due to overplotting. Some NAICS codes, such as extraterritorial entities (embassies, etc), are not represented because they did not have any input products with tariffs .

D Additional Analysis

Tables A2 and A3 report the effects of treatment on actions taken in support of the trade war. Table A4 presents the effects of treatment on the number of actions taken to either oppose or support the trade war.

In the main text, we report results from a simple logistic regression of whether the respondent selected an anti-tariff political action on the treatment they received. However, because the outcomes in our experiment are dependent (respondents first choose what types of outcomes to see in terms of supporting or opposing the trade war), to fully model the treatment effects we need to examine the dependency between the first outcome and the second. We present this analysis below. As with the conditional effects we report in the main text, our two-stage analysis also concludes that our treatment had completely null effects.

To model the dependent outcomes, we use instrumental variable regression to jointly estimate the ATE for the first stage (selecting a type of outcome to see) and the second stage outcomes (what kind of particular actions to take). For our main specifications for the second stage, we use a logistic regression in which our outcome variable is a dummy variable for whether the respondent took any action to oppose the trade war, and our treatment variable is a dummy variable for whether we provided the respondent with our static treatment about their firm's vulnerability to tariffs.

We model our two outcomes Y_1 (what type of outcome to see) and Y_2 (whether to select political activity of the given type) using the following distributions given a binary-coded treatment indicator $D = 1$:

$$Y_1 \sim \text{OrdLogit}(\alpha_1 - \gamma_1 + \beta_1 D) \tag{2}$$

$$Y_2 \sim \text{Normal}(\alpha_2 + \beta_2 D + \beta_3 Y_1) \tag{3}$$

Table A2: Treatment Effects on Actions Taken to Support Trade War

	Facebook	Congress	Petition	Invite	Any
(Intercept)	-1.961***	-2.429***	-26.566	-1.333***	-1.621***
	(0.230)	(0.205)	(19876.903)	(0.137)	(0.150)
Dynamic	0.109	-0.109	0.000	-0.110	0.115
	(0.231)	(0.298)	(28266.417)	(0.199)	(0.210)
Dynamic AND Static	-0.316	-0.292	0.000	-0.572***	-0.284
	(0.249)	(0.308)	(28045.041)	(0.215)	(0.224)
Static	-0.201	-0.516	0.000	0.023	-0.242
	(0.244)	(0.328)	(28132.139)	(0.194)	(0.222)
Num.Obs.	1279	1279	1279	1279	1279
AIC	946.8	630.2	8.0	1224.2	1095.6
BIC	972.6	650.8	28.6	1244.8	1116.2
Log.Lik.	-468.395	-311.115	0.000	-608.082	-543.805

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Effect of Receiving Any Treatment on Actions Taken to Support Trade War

	Facebook	Congress	Petition	Invite	Any
(Intercept)	-1.894***	-2.429***	-26.566	-1.333***	-1.621***
	(0.166)	(0.205)	(19876.903)	(0.137)	(0.150)
Dynamic OR Static	-0.128	-0.295	0.000	-0.201	-0.128
	(0.194)	(0.245)	(22966.840)	(0.161)	(0.176)
Num.Obs.	1279	1279	1279	1279	1279
AIC	944.2	627.7	4.0	1228.6	1095.6
BIC	954.5	638.0	14.3	1238.9	1105.9
Log.Lik.	-470.115	-311.860	0.000	-612.309	-545.817

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Treatment Effects on Count of Actions Taken

	Oppose	Support	Oppose	Support
(Intercept)	0.988***	0.645***	0.988***	0.645***
	(0.077)	(0.053)	(0.077)	(0.053)
Dynamic	-0.070	-0.040		
	(0.109)	(0.076)		
Dynamic AND Static	-0.120	-0.216***		
	(0.108)	(0.075)		
Static	-0.034	-0.092		
	(0.109)	(0.075)		
Dynamic OR Static			-0.075	-0.117*
			(0.089)	(0.062)
Num.Obs.	1279	1279	1279	1279
AIC	4448.6	3518.1	4445.2	3519.8
BIC	4474.3	3543.8	4460.7	3535.3
Log.Lik.	-2219.283	-1754.027	-2219.601	-1756.904

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We model Y_1 as an ordered logit distribution, as there is an intermediate category in which respondents could choose to see both support and oppose outcomes. We model Y_2 as a Gaussian outcome, as we use factor scores to collapse the four to five types of political activity that a respondent could choose to a single number. We include the first stage outcome Y_1 as a predictor in the equation for Y_2 so that we can account for the effect of the choice that a respondent makes in the first stage on the probability of seeing outcomes of different types in the second stage.

In terms of treatment effects, β_1 is the ATE for the first-stage outcome (selecting a given type of political activity, either opposing or supporting the trade war, or both), β_2 is the conditional ATE for the second-stage outcome, and the sum of $\beta_1 + \beta_2$ is what we report as the combined effect. For example, if both $\beta_1 > 0$ and $\beta_2 > 0$, then the treatment made our respondents more likely to see oppose trade war outcomes and more likely to select such a type of political activity conditional on seeing it. On the other hand, if $\beta_1 < 0$ and $\beta_2 > 0$, then the treatment made respondents less likely to select to see oppose trade war activities, but if respondents did select to see them, they became more likely to actually pick one relative to control. Reporting all of these coefficients allows us to capture all of these nuanced ways that the treatment could affect the outcome.

To ensure that both β_1 and β_2 are on the same scale (probability of change in the outcome), we convert β_1 to the marginal effect of D on Y_1 using the `marginaleffects` package in R [55]. Because we estimate this model in a Bayesian framework using Stan, we can combine coefficients by summing over posterior draws of these parameters. We report posterior means and quantiles from these models in Table A5 and visualize them in Figure A6.

In H1, we had hypothesized that, on average, providing managers with information about their tariff exposure would increase their likelihood of taking political action. This is not what we found. In Figure A6, we separate out our overall treatment effects both by the stage of the outcome (interest in seeing the opposition list, and then interest in an opposition item from that list) as well as by the format of the treatment we provided the respondent (static, dynamic, or both). Since the combined (1st + 2nd stage) effect represents the probability that a respondent opposes the trade war and then takes action to express their views, this estimand most closely approximates how information motivates managers to oppose tariffs and then act on their opposition.

The top row illustrates our most basic finding: seeing any form of our treatment (static or dynamic) had no effect on a respondent's first- or second-stage outcome, or the combined probability that they chose both. Unsurprisingly, when we break out results out to look only at the static or dynamic treatments in isolation, we see similar results: neither treatment induced any change in our respondents' behavior. Only in the last row — looking at respondents who received both dynamic and static treatments — do we see any possible effects. As we found in the main text, this combined treatment was most powerful. This treatment combination did not have any effect on a respondent's

[55] Arel-Bundock, Diniz, and Greifer (2022)

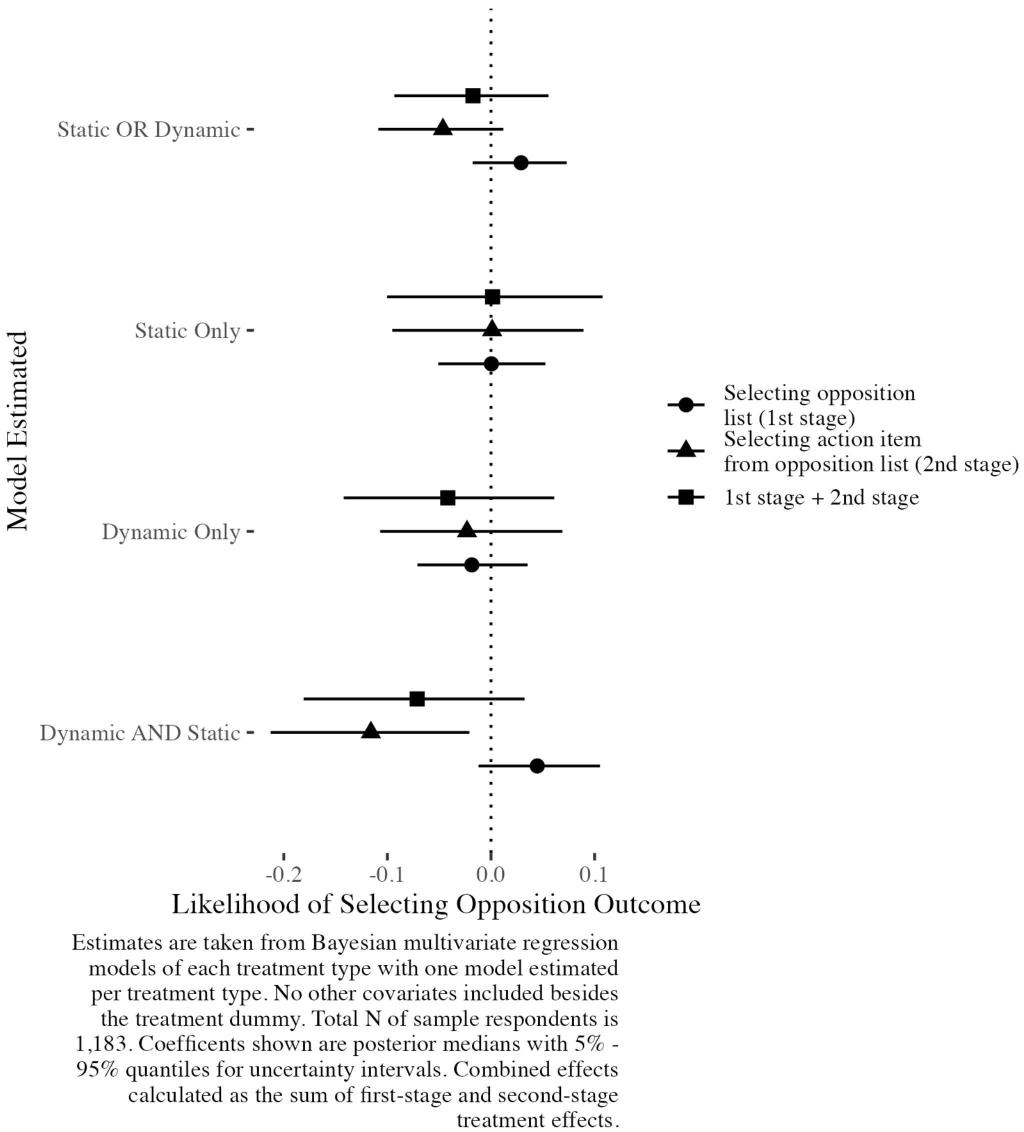


Figure A6: Treatment Effects from Two-Stage Analysis (Table A5) support or opposition to the trade war (1st stage), but it did have an effect on whether they took political action conditional on opposing the trade war. As with the main analysis, it was in the opposite direction of our intention: conditional on opposing the trade war, respondents who received our combined treatments were *less* likely to act on their views. It seems that the information we provided did not persuade them to change their opinions about the trade war, but it could have made them think the extent of economic damage was not as bad as they had previously thought or that political action would be unlikely to bring about change in policy. However, when we look at the combined first- and second-stage outcomes, the results are again null. People who received our combined treatment are not, overall, any more or less likely to take political action to oppose the trade war. We conclude that spreading information of the sort we provided is unlikely to have any effect on anti-tariff political action.

It is also possible to also estimate these effects using mediation analysis [56]; these estimated effects are substantively similar although they employ OLS regressions instead of ordinal models. We report these effects in Table A6 as an alternative way of estimating the multiple outcomes, though we note this package does not report 1st stage outcomes. Calculating mediation effects with the R package `mediate` shows that the average different effect (equivalent to our second-stage effect) is -0.07 (-0.15, 0.01) for the dynamic only treatment, which is very close to the effect reported in Table A5 at -0.023. As in Table A5, the combined effect (or total effect) of the dynamic only treatment is statistically insignificant with an estimated treatment effect of -0.06 (-0.173, 0.05). Similarly, the average direct effect (2nd stage outcome) for our static only treatment is -0.06 (-0.157, 0.04) compared to a value of 0.01 (-0.095, 0.089) in Table A5.

[56] Imai, Keele, and Tingley (2010)

Table A5: Coefficient Values for Figure A6

Treatment Coding	Outcome	ATE
Dynamic AND Static	1st Choice: Select List	0.045 (-0.012, 0.105)
Dynamic AND Static	1st stage + 2nd stage	-0.071 (-0.181, 0.032)
Dynamic AND Static	2nd Choice: Select Action on List	-0.116 (-0.213, -0.021)
Dynamic Only	1st Choice: Select List	-0.019 (-0.071, 0.035)
Dynamic Only	1st stage + 2nd stage	-0.042 (-0.142, 0.061)
Dynamic Only	2nd Choice: Select Action on List	-0.023 (-0.107, 0.069)
Static OR Dynamic	1st Choice: Select List	0.029 (-0.018, 0.073)
Static OR Dynamic	1st stage + 2nd stage	-0.017 (-0.093, 0.055)
Static OR Dynamic	2nd Choice: Select Action on List	-0.046 (-0.109, 0.012)
Static Only	1st Choice: Select List	0 (-0.051, 0.053)
Static Only	1st stage + 2nd stage	0.002 (-0.1, 0.108)
Static Only	2nd Choice: Select Action on List	0.001 (-0.095, 0.089)

Coefficients from Bayesian multivariate model of multi-stage outcomes with one model estimated for each type of treatment shown in column Treatment Coding. The total number of observations is 1,183 and there are there are no additional covariates besides the treatment dummy. Each coefficient is equal to the regression coefficient with a treatment vector with the appropriate coding. All model coefficients are shown besides ancillary parameters (e.g., cutpoints and residual variance). Estimates are calculated as the mean of the posterior distribution along with the 5% to 95% posterior interval. All Rhats below 1.1 indicating strong convergence.

Table A6: Mediation Calculation (Comparable to Table A5)

Treatment Coding	Outcome Type	ATE
Static OR Dynamic	2nd Choice: Select Action on List	-0.045 (-0.134, 0.04)
Static OR Dynamic	1st stage + 2nd stage	-0.0036 (-0.137, 0.07)
Static AND Dynamic	2nd Choice: Select Action on List	-0.119 (-0.225, -0.01)
Static AND Dynamic	1st stage + 2nd stage	-0.078 (-0.21, 0.07)
Static Only	1st stage + 2nd stage	-0.038 (-0.156, 0.08)
Static Only	2nd Choice: Select Action on List	-0.059 (-0.157, 0.04)
Dynamic Only	2nd Choice: Select Action on List	-0.071 (-0.168, 0.03)
Dynamic Only	1st stage + 2nd stage	-0.059 (-0.173, 0.05)

Coefficients from R mediation package to calculate combined (1st stage + 2nd stage) versus 2nd stage effects. These are equivalent to total and direct effects in mediation terms. Note that 1st stage effects are not included in the calculation.

E Additional Pre-Registered Hypotheses

The main hypothesis we pre-registered but do not discuss in the main text concerns the relationship between a firm's exposure to tariffs and their response to treatment. In our pre-registration, we predicted:

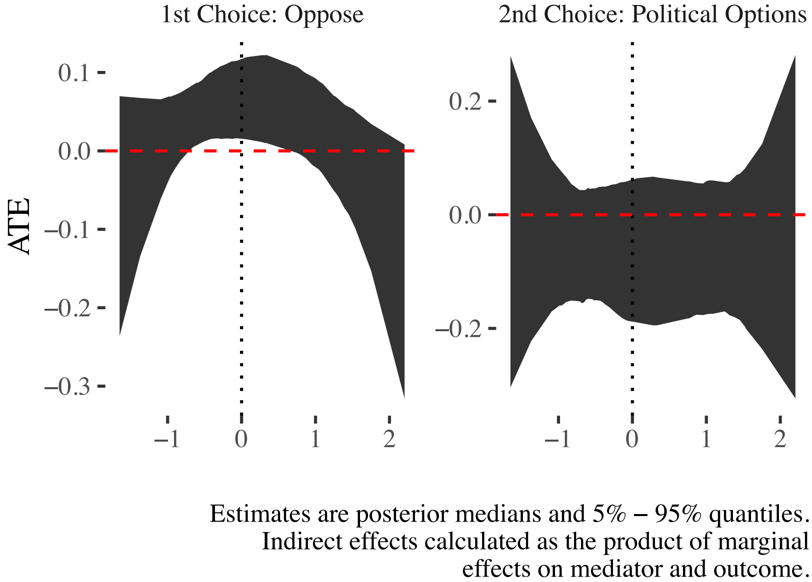
H3. The effect of presenting firms with information about the possible rise in a firm's input costs is likely to have a concave quadratic relationship with respect to a firms' vulnerability to tariffs.

In other words, we expected that our treatment would not have a very large effect for firms who were highly affected (and probably were already aware of these issues) or for firms who were not very affected by tariffs (for whom these issues seemed irrelevant). Our treatment would matter most for firms who were somewhat affected but perhaps hadn't realized it.

The results appear in Figure A7.

However, we choose not to feature these in the main text due to issues of causal inference. Exposure to tariffs is not only a pre-treatment covariate but also the content of the information we communicated as part of our treatment. Individuals are likely to react differently when they are told different information. For this reason, it is impossible for us to distinguish whether our information had a greater effect for some types of respondents than for others, or whether different information had different effects. But since we pre-registered this hypothesis, and have the ability to test it, we include these results.

We also pre-registered hypotheses for other versions of the treatment (such as a pro-free trade ideological appeal) that we later decided to cut due to limitations of statistical power.



Plot shows LATEs for the two stages of the opposing trade war outcomes conditional on the respondents' firms' total number of tariffs as calculated from our BEA industry exposure data. The scale of the x axis is in standard deviations of the number of tariffs.

Figure A7: H3: Conditional Treatment Effects by Level of Exposure to Industry Tariffs

F Additional Interactions

In this section, we include some additional treatment interactions. Specifically, we examine whether a firm's prior actions related to tariffs precluded them from responding to the treatment because they already had ample information. Tables A7 and A8 show an interaction between a binary variable for whether the firm had taken prior action related to tariffs (Tariff Action) and the treatment across outcome types. As can be seen, the coefficients are generally negative, suggesting that if a relationship exists, those who had prior experience with tariffs were less responsive to the treatment, but generally the coefficients are too small and the standard errors to reach any substantive conclusions.

In Figure A8 we show an the predicted treatment and control responses for any oppose trade war outcome subset by the ideological composition of the respondent firm's culture. We can see that for both managers and rank-and-file employees the treatment was modestly negative but not statistically different than the control group.

Table A7: Disaggregated Treatment Effects by Firm Prior History on Tariff Actions

	Facebook	Congress	Petition	Invite	Governor	Any
(Intercept)	-1.702***	-1.310***	-26.566	-1.360***	-4.078***	-0.867***
	(0.179)	(0.158)	(22987.705)	(0.160)	(0.504)	(0.141)
Dynamic	-0.015	-0.092	0.000	0.010	0.819	-0.058
	(0.253)	(0.226)	(32409.031)	(0.225)	(0.608)	(0.201)
Dynamic + Static	-0.113	-0.348	0.000	-0.239	0.790	-0.285
	(0.255)	(0.234)	(32182.787)	(0.233)	(0.608)	(0.205)
Static	0.053	-0.251	0.000	0.206	0.405	-0.135
	(0.250)	(0.232)	(32442.287)	(0.220)	(0.652)	(0.203)
Tariff Action	0.350	0.835**	0.000	-0.078	1.983**	0.564*
	(0.340)	(0.288)	(47599.935)	(0.338)	(0.628)	(0.276)
Dynamic:Tariff Action	-0.038	-0.746+	0.000	-0.552	-1.027	-0.332
	(0.493)	(0.447)	(68623.938)	(0.531)	(0.833)	(0.406)
Dynamic + Static:Tariff Action	-0.075	-0.439	0.000	0.656	-0.860	-0.148
	(0.500)	(0.445)	(68103.703)	(0.467)	(0.818)	(0.406)
Static:Tariff Action	0.076	0.357	0.000	0.009	-0.156	0.378
	(0.482)	(0.418)	(68639.650)	(0.472)	(0.833)	(0.397)
Num.Obs.	1248	1248	1248	1248	1248	1248
AIC	1119.7	1275.5	16.0	1268.3	455.7	1515.2
BIC	1160.7	1316.5	57.0	1309.3	496.8	1556.3
Log.Lik.	-551.826	-629.735	0.000	-626.158	-219.869	-749.616
F	0.698	4.663	0.000	1.196	4.177	3.101
RMSE	0.37	0.40	0.00	0.40	0.21	0.45

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Each model is one of the pre-registered outcomes in opposition to the trade war. Tariff Action is whether the respondent's firm had previously taken action on tariffs.

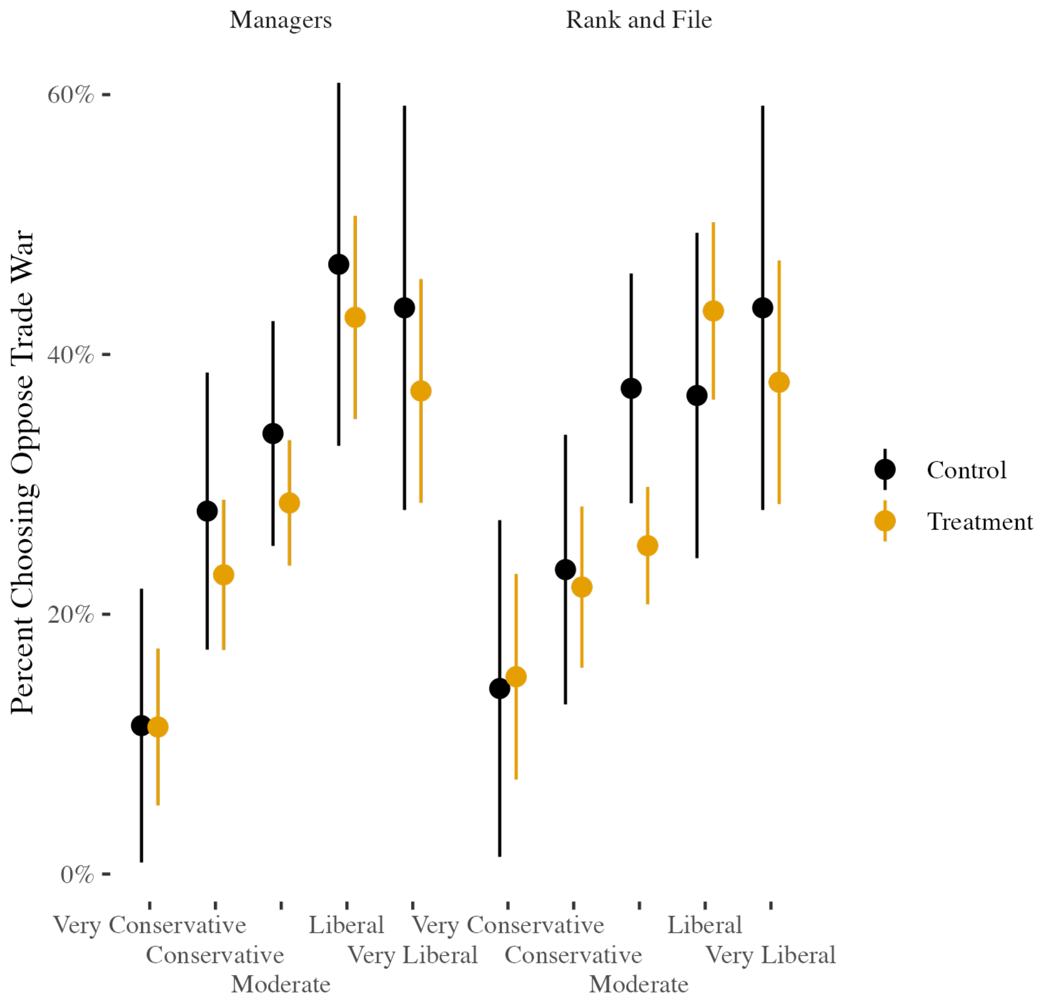
Table A8: Collapsed Treatment Effects by Firm Prior History on Tariff Actions

	Facebook	Congress	Petition	Invite	Governor	Any
(Intercept)	-1.702***	-1.310***	-26.566	-1.360***	-4.078***	-0.867***
	(0.179)	(0.158)	(22987.705)	(0.160)	(0.504)	(0.141)
Collapsed	-0.024	-0.228	0.000	-0.001	0.689	-0.158
	(0.206)	(0.185)	(26476.115)	(0.184)	(0.545)	(0.164)
Tariff Action	0.350	0.835**	0.000	-0.078	1.983**	0.564*
	(0.340)	(0.288)	(47599.935)	(0.338)	(0.628)	(0.276)
Collapsed:Tariff Action	-0.010	-0.242	0.000	0.084	-0.685	-0.028
	(0.397)	(0.342)	(55429.463)	(0.391)	(0.699)	(0.323)
Num.Obs.	1248	1248	1248	1248	1248	1248
AIC	1112.6	1276.6	8.0	1269.0	449.2	1513.1
BIC	1133.1	1297.1	28.5	1289.6	469.7	1533.6
Log.Lik.	-552.315	-634.295	0.000	-630.520	-220.607	-752.531
F	1.287	7.624	0.000	0.022	9.285	5.286
RMSE	0.37	0.41	0.00	0.40	0.21	0.45

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Each model is one of the pre-registered outcomes in opposition to the trade war. Tariff Action is whether the respondent's firm had previously taken action on tariffs.

Figure A8: Treatment Effects by Political Culture of Firm among Managers and Rank and File Employees



Nor do we observe consistent differences between conservatives and liberals in terms of the treatment's effectiveness. For these reasons, we do not believe that the treatment differentially affected the outcome by partisan subgroups.

G Prior Tariff Action and Treatment

In this section we implement some descriptive statistics and treatment models that explore to what extent taking a prior political action may have affected our respondents'

Table A9: Proportion Selecting Experiment Outcomes by Prior Tariff Action

Outcome	Prior Tariff Action	Proportion Choosing Outcome
Any Selection	No	27.2%
Any Selection	Yes	39.2%
Contact Congress	No	18.6%
Contact Congress	Yes	30.8%
Donate to Congress	No	3.9%
Donate to Congress	Yes	9.2%
Donate to Governor	No	2.9%
Donate to Governor	Yes	11%
Invite Others	No	20.4%
Invite Others	Yes	20.1%
Join Facebook Group	No	15.2%
Join Facebook Group	Yes	20.1%

Table shows proportion selecting different kinds of experimental outcomes given whether the respondents had said they had previously taken action about tariffs.

willingness to interact with the treatment. In brief, while respondents whose firms had taken prior action on tariffs were more likely to view political outcomes (Table A9), we do not find that the treatment effects were any different when we control for prior tariff action (Table A10). This is what we would expect, as in expectation, treatment and control groups should have similar compositions of active and inactive firms.

We also show the descriptive reasons for why managers reported that they did not select any of the possible political action types in our survey in Figure A9. Some respondents in all categories said that they had already taken action on the trade war. However, these respondents are a minority of the reasons given. The most popular reasons are that (1) the political activities would not change anything, (2) that the firm is not affected by the trade war, and (3) that they are worried about backlash if they take a position in the trade war. Those respondents who chose to see only opposition

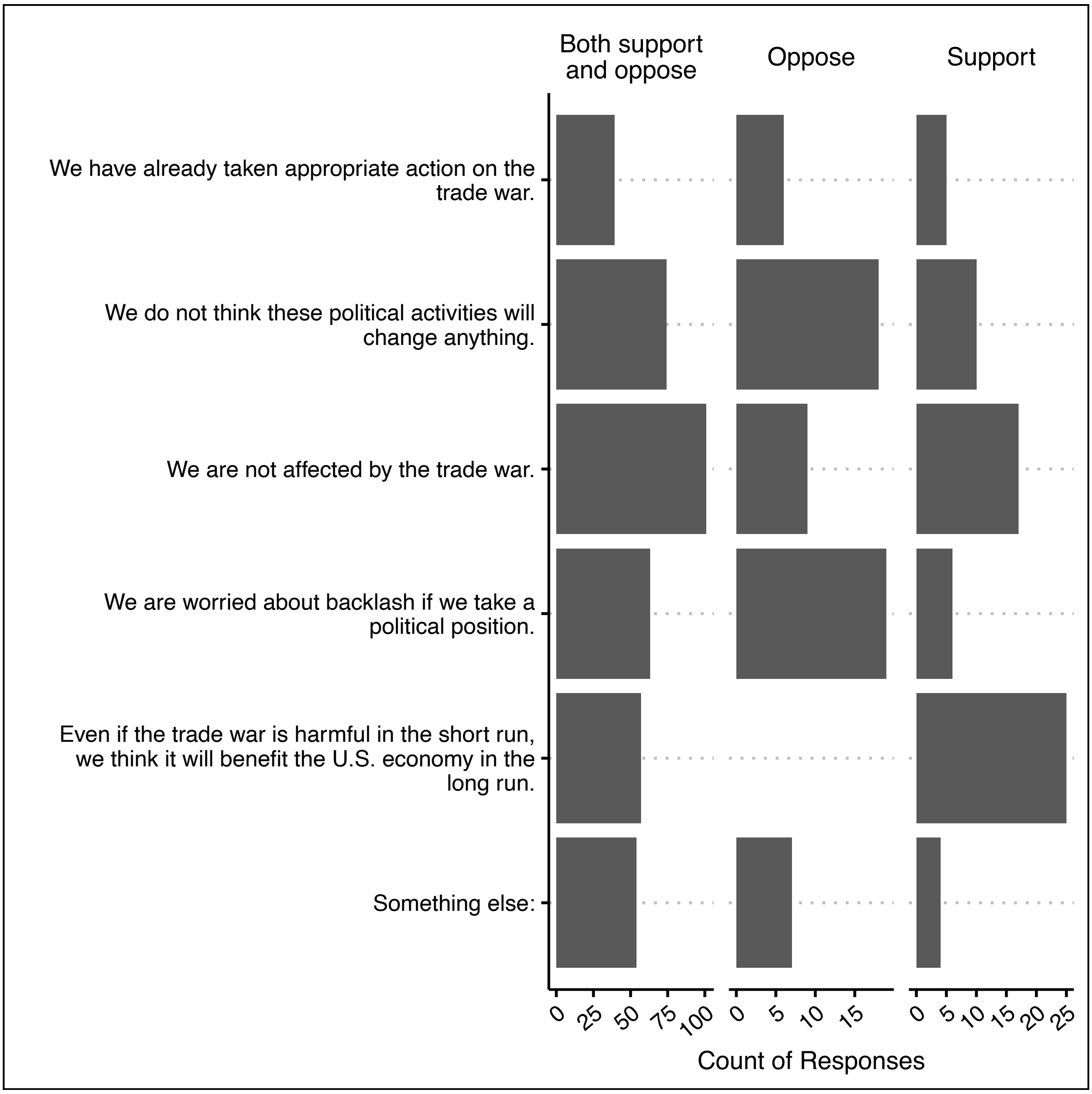
Table A10: Effect of Treatments when Controlling for Prior Tariff Action

	Facebook	Congress	Petition	Invite	Governor	Any
(Intercept)	-1.700***	-1.260***	-26.566	-1.375***	-3.758***	-0.862***
	(0.160)	(0.139)	(20917.642)	(0.146)	(0.330)	(0.127)
Dynamic	-0.024	-0.287	0.000	-0.087	0.290	-0.137
	(0.217)	(0.194)	(28563.148)	(0.203)	(0.401)	(0.175)
Dynamic + Static	-0.132	-0.472*	0.000	-0.081	0.328	-0.323+
	(0.220)	(0.199)	(28358.979)	(0.201)	(0.395)	(0.177)
Static	0.072	-0.145	0.000	0.209	0.292	-0.040
	(0.214)	(0.190)	(28586.187)	(0.195)	(0.401)	(0.173)
Tariff Action	0.343+	0.665***	0.000	-0.016	1.437***	0.545***
	(0.175)	(0.155)	(24390.132)	(0.171)	(0.273)	(0.144)
Num.Obs.	1248	1248	1248	1248	1248	1248
AIC	1113.8	1276.5	10.0	1268.1	452.2	1512.5
BIC	1139.4	1302.1	35.6	1293.8	477.8	1538.1
Log.Lik.	-551.877	-633.239	0.000	-629.055	-221.098	-751.236
F	1.181	6.109	0.000	0.762	7.076	4.569
RMSE	0.37	0.40	0.00	0.40	0.21	0.45

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Each model is one of the pre-registered outcomes in opposition to the trade war. Tariff Action is whether the respondent's firm had previously taken action on tariffs.

outcomes were the most likely to be worried about facing backlash over taking a position on the trade war.

Figure A9: Reasons Why No Political Action Was Chosen



Plot shows the count of responses for respondents who did not select any opposition or support for the trade war outcomes in the survey. Responses are shown by whether respondents wanted to see political actions to (1) support the trade war options, (2) oppose the trade war options, (3) or both types of options. If they do not click on any of the political actions provided, they are asked on the following screen why no action was taken.