Supplementary Appendix

CueAnon

Contents

A Observational Analysis: Quantity and Tone of Candidate Coverage

A.1 Nexis Uni Article Collection Instructions

Instructions for Nexius Uni News Articles about 2020 Candidates

1. Log on to Nexis Uni

- Visit the library's website and click on "Nexis Uni." You will be taken to a log in page where you can put in your university key to access the site.

2. Search for candidates

- Using the big search bar, enter the candidate's `name` from the CSV file (e.g. 'lauren witzke').
- Once you are on the results page, on the top left you should see a header that says "Results for `candidate name` and"Actions" in blue and a down arrow. Click on the down arrow and select the first option "Run search as terms & connectors." This will search for the full name rather than "lauren" or "witzke." The page will refresh with new results.
- On the left sidebar find "Timeline" and click it. Then enter the start date as 1/1/2020 and the end date as 11/2/2020. The page will refresh with new results.
- Then find "Publication Type" on the sidebar and select "Newspapers." The page will refresh with new results. If this option is not available, that means there are no newspaper articles about the candidate. Stop and proceed to step 3.
- Find "Language" on the sidebar and select "English".
- Now, you've subset appropriately. Because news articles may be about the candidate or possibly about other people with the same name (especially if the name is common), quickly skim each article to ensure it's about the candidate.
  - This does not need to be a long process—if the headline is about politics, then that is good enough. If that is unclear, look at the excerpt—often it will say something like "Republican candidate, Lauren Witzke. . . " which is sufficient to meet the criteria.
  - If the article is about the candidate, check the box next to the article. Continue for all articles that meet the filtered critera. The checks will persist even as you go to the next results page.
  - If, in the process, you discover that the candidate goes by some other name or nickname, follow the above/below steps and include those articles as well.

3. Updating the CSV and Box

- If there are no articles, find that candidate's row and record 0 in the csv in the `total_news`. column. Otherwise. . .
- When you've checked all articles about the candidate, start downloading them. You can download the checked articles by using the `download` button toward the top—this is the down

arrow into a box. Note: You can only download 100 articles at a time. If the candidate has more than 100 articles, please repeat these steps in batches of 100.

  - On the screen that pops up ensure you check the following options:
    * Full documents
    * Rich Text Format
    * Save as individual files
    * Rename the Filename the candidate's name where spaces are replaced by the _ key and all letters in lowercase e.g. "lauren_witzke"
  - This will download a zip file. Open the zip file and add the contents of the unzipped folder to the `NexisFolders321` folder in Box as in the example folder that is already there.
- Check to make sure there are no duplicates in the candidate folder—these will normally be denoted by your system by appending a (1) or (2) etc to the end of the filename. For example, you might see "Article Title" and "Article Title (1)". Put any duplicates (aka any with an numeric append) in the trash but keep the original in the folder.
- Every time you download a file, it will also download a file that simply lists the articles you downloaded called `candidate_name_doclist`. Delete this file as well.
- Once you've cleaned up everything, count how many files are left in the folder. If you are on mac, you can do this without manually counting anything—just select all articles in the folder and right click. Then, the first item in the menu will say "New Folder With Selection (XXX Items)". There is probably something similar on Windows. Record that number in the csv under `total_news` for that candidate.
  - Note: You cannot simply record the number from the checked boxes on the website as it will include duplicate articles.

A.2 Nexis Uni Article Coding Instructions

Instructions for Coding Articles

Our ultimate goal is to determine whether the articles Nexis Uni has labeled "negative news" are *negative in tone toward the target candidate* we are interested in. That is, even if the article is negative in tone overall, does that negativity apply to the candidate of interest?

Articles and spreadsheet

In the folder `NexisFolders_1220` , you find a spreadsheet called `articles_handcode.csv` . You'll see five columns. The first column, `name` will direct you to the appropriate candidate folder where you can find the assigned article. The column `title` will tell you which article in the candidate folder to read. You can ignore the next two columns called `neg` and `qcand` . The final column `negative` is where you'll record whether the article is *negative in tone toward the target candidate*. 1 means it is negative toward the target candidate. 0 means it is not.

How to determine negativity

We are not interested in whether an article is negative overall, but rather, whether the article's negativity applies to the target candidate (the candidate whose folder the article came from). To further clarify: we want to know if the *article's author* is negative toward the candidate. We don't care if the author reports about someone else saying something negative about the candidate.

As an example, there is an article in our sample titled "Senate candidate changes story about gun claim." Nexis Uni has classified it as negative news. Reading the article, I would classify the following excerpt as negative about Peggy Hubbard:

> "After spawning controversy when she said she brought a handgun to a debate at a suburban high school last month, Republican Senate hopeful Peggy Hubbard shared a different version of that tale during a televised forum Tuesday."

However, this article is in the folder for a candidate named **Robert Marshall**. The article says this about Marshall:

> After asking Hubbard about the Hinsdale Central forum, Ponce asked all the candidates about gun control laws. One of them, Robert Marshall, took the opportunity to accuse Hubbard of lying about what happened at the forum. "Mrs. Hubbard has two versions of what happened, and it's all on tape," Marshall said. "So one of her versions is false."

This passage does not necessarily seem to be negative about Marshall. Rather, it just recounts his actions at the debate (which themselves might be negative or mean), but the author of the article seems to be reporting the facts of what happened without making any judgment about Marshall.

Were the target candidate Peggy Hubbard you would code this as 1 in the negative column. However, the target is Robert Marshall, so you would code this article as 0 in the negative column since it is not actually negative *about Robert Marshall*. If later in the article, the author had noted that Peggy Hubbard said "Robert Marshall was a big jerk," you *still code this as 0* because the author was not being negative toward Marshall.

Ultimately, these are subjective decisions, and another person could disagree with your label. That's fine and to be expected. Just trust your gut.

How to code articles with many references to the candidate

It is likely that these articles will mention the target candidate multiple times. Some of these references may be neutral or factual. Others may be negative. The rule of thumb here is like that saying "one bad apple spoils the whole bunch." *Any negativity toward the candidate*, even if it's just once out of five times is enough to code the article as negative. Even if the article was positive toward the candidate at one point, any negativity toward them is sufficient to code it as 1 for negative.

What this means is that you can actually save yourself some time and quit reading an article after the first negative reference to the candidate. However, if there are no negative references, you'll have to read the whole thing through to be sure.

A.3 Ballotpedia Candidate Scraping and Data Collection Instructions

We created an automated web scraper that went through Ballotpedia.com and tried to identify all candidates who ran in House and Senate primaries or general elections in 2020, as well as some information about those candidates. Unfortunately, the scraper isn't perfect nor is Ballotpedia, so there were several places where we were unable to capture information we are interested in.

In the excel file, you will find a list of candidates as well as columns with variables we are interested in. Each row is a candidate, and in each row, there is something missing—believe it or not, this is a small minority of all the candidates that ran.

Our hope is that you'll be able to help us fill in the NAs. Here is the process:

1. Quickly look at the candidate's name. Often, there isn't anything wrong with the name, but occasionally, the scraper grabbed something that wasn't actually a candidate. For example, in row 18, the name is "Candidate Conversation." Clearly, this was a mistake and isn't a candidate.
    a. **Action:** Delete the entire row.
2. Quickly check the link. Ballotpedia candidate links all have a similar format and should look something like this: https://ballotpedia.org/Wendell_Crow. However, sometimes there is a mistake where we only capture part of the link. For example, in row 30, all that appears is "/Barry_Hess"
    a. **Action**: If it is a candidate's name, try to visit their Ballotpedia page by adding https://ballotpedia.org to the front. If that works, replace the bad link with the full, working link. **Please note: If the link was broken,** there may still be information about the candidate's office, party, etc in the row. **This information will be incorrect.** Please continue to follow the process and verify/replace all missing and entered values for the remaining columns.
    b. **Action**: If it's not a candidate at all, delete the row. If there is a candidate, but the link was broken because of capitalization issues (e.g. /Barry_hess instead of /Barry_Hess), try searching for the candidate's name within Ballotpedia. If the candidate did run in 2020, fix the link and update the information.
3. Often, the sex of the candidate is missing because Ballotpedia doesn't have any information on whether the candidate identifies as male or female.
    a. **Action**: Do a quick google search for the candidate and see if you can find this information in any news articles where they use the candidate's pronouns. Don't spend too much time on this. If you find their pronouns, code them as M or F as appropriate. If their pronouns are neither he/his nor her/hers, then code this variable as "other." If you cannot quickly find their pronouns, just leave them as NA.
4. Prev_off is a variable that takes on the value of 1 when the candidate has held previous office and takes on a value of 0 if they have not.
    a. **Action**: if the prev_office value is NA…

i. If the candidate held prior office, there is often a section in the box called "prior offices." If that section exists, then code prev_off as 1. If this box does not appear…
ii. See if the candidate is currently in office in the box on the right. If it says US House or US Senate and their "tenure" began before 2021, code as 1. Otherwise…
iii. Quickly read the biography text about the candidate. If it lists previous elected office at any level of government, code as 1. Otherwise code as 0.

b. For example, Ted Terry in row 51 is NA. On his page, we can see that there is no prior offices section in the box. We can also see in the box he began his term on the Dekalb County Commission in 2021—so this is a new office not a previous office. We can see in the biography that there is no information about any previous elected office before this one. Therefore, we would code this as 0.

5. If party is NA, that information can usually be found in the box or in the overview text about the candidate.
    a. **Action**: Enter the first letter of the party in the party column.
6. Office looks at whether the person ran for the House or the Senate in 2020. If this is missing, you can often find this information in the overview section. Often this information is missing when the candidate dropped out or lost the primary and then ran for something else.
    a. **Action:** Please enter House or Senate accordingly.
7. State and District. This information can often be found in the overview text about the candidate.
    a. **Action**: Please enter the full state name in the state column and the numeric value of the district they ran in. For example, Ballotpedia will say that someone ran for Colorado's 2nd congressional district. You would enter Colorado and 2. If the district is an "At Large" district, please enter 1 in the district spot. If the candidate ran for Senate, please enter 99 in the district space.
8. Ge_cand is about whether a candidate ran in the November 3rd *general* election (meaning that they won their primary and advanced to the general).
    a. **Action**: Look at the candidate overview text. Often this will tell you if the candidate ran in a primary or general election and whether they won or lost. Mark this as 1 if the candidate competed *in a House or Senate* general election (including write ins or independent bids). Otherwise, mark it as 0. Note: If the candidate ran for the House but lost and then ran for State Senate or something, this would be coded as 0. The box on the right may have information about the candidate's last election, **but be careful**—especially if the candidate ran for a different office than House or Senate.

A.4 Data and Results

Table A1: Examples of human sentiment-coded newspaper text for both QAnon-supporting and non-supporting candidates.

Candidate	QAnon	Negative	Text
Marjorie Taylor Greene	Yes	Yes	At least one of them, **Marjorie Taylor Greene** of Georgia, will probably join the House next year. Despite her QAnon advocacy and a history of racist and Islamophobic rants on social media, Mr. Trump hailed her as a "future Republican star."
C. Wesley Morgan	Yes	No	As of Friday afternoon, those who have filed to run for state or federal offices in Kentucky, which has to be done through the state secretary of state's office in Frankfort, include...Mitch McConnell of Louisville and **C. Wesley Morgan of Richmond**.
Peggy Hubbard	No	Yes	**Hubbard** drew controversy for publicly claiming she took a gun and ammunition into a suburban school for a candidate forum. **Hubbard** later changed her story, telling the Daily Herald she "misspoke" and actually had left the gun locked in her car.
Kim Klacik	No	No	The RNC featured a large number of speakers including, as reported by CBS, Maryland Congressional candidate **Kim Klacik**, Pennsylvania congressional candidate Sean Parnell and North Carolina congressional candidate Madison Cawthorn.

Observational Evidence: Quantity and Tone of Candidate Coverage

Our objective in this section is to determine whether candidates who support QAnon receive more media coverage and whether that coverage is more negative.

Data and Methods

We begin by examining variation in news coverage of QAnon-supporting candidates and their non-QAnon supporting peers. To do so, we collected data on 3,632 candidates identified by `Ballotpedia.com` as having run in either a congressional House or Senate primary in 2020. Along with their name and the office they were running for, we also captured information about their sex, whether they had previously held elected office at either the state or federal level, their party, the state (and if applicable, the district) in which they were running, whether they won their primary race, and their social media account information. We supplemented this data with an indicator for whether the candidate had ever supported QAnon, as identified by Media Matters (Kaplan 2020), as well as the Cook Partisan Voting Index of the state and/or district. We also sourced state or district level demographics from Social Explorer.

Candidates who support QAnon are different from their non-supporting peers, which we show in the left half of Table A2. For example, QAnon-supporting candidates are significantly more likely to be female and less likely to be incumbents. We also find that QAnon-supporting candidates run in districts that are about 7 points more Democratic on average than non-supporters, which provides some evidence that these candidates are not entering races in overwhelmingly Democratic districts expecting to lose. The differences we've highlighted are likely correlated with media coverage in important ways. To address this concern and achieve balance across groups, we constructed a matched set of QAnon-supporters and otherwise similar candidates who did not support QAnon based on the covariates we collected. Following Darr, Hitt and Dunaway (2018), we created the matched set through the use of Genetic Matching (Diamond and Sekhon 2013). The genetic matching yielded a sample with 264 unique (unweighted) candidates.[1] In the right half of Table A2, we present covariate balance and p-values from t-tests and bootstrapped Kolmogorov-Smirnov tests. The smallest p-value is 0.80, indicating that the distribution of each covariate is statistically similar between groups.

After creating this matched subset, we collected all newspaper coverage of each candidate in our sample between January 1 and November 2, 2020 (just before Election Day). We manually searched Nexis Uni to collect all newspaper articles—national and local—that referenced each candidate at least once.[2] We collected articles from a variety of national sources, like the the *New York Times* and the *Guardian*, as well as local sources like *Alaska Dispatch News* (AK) and the *Pueblo Chiefton* (CO).[3] From this large set, we ran-

[1] We conducted this matching in two stages, first sub-setting to a small number of candidates to facilitate data collection, and then matching a second time among that subset.

[2] Please see Appendix A.1 for full data collection criteria. In summary, we searched each candidate's first and last name, set the time frame to January 1-November 2, 2020, we set the publication type to newspapers, and the language to English. Each article was then manually screened to ensure it was about the candidate, rather than someone with the same name.

[3] This approach limits our data collection to the Nexis Uni database. Although Nexis Uni is widely

Table A2: Matching Balance

	Before Matching			After Matching		
	QAnon Support mean	Non-Supporter mean	Boostrapped KS Test *p*-value	QAnon Supporter mean	Non-Supporter mean	Boostrapped KS Test *p*-value
% Female	0.39	0.25	0.01	0.39	0.39	1.00
% Previous Officeholder	0.03	0.18	0.00	0.03	0.03	1.00
% Senate Bid	0.09	0.14	0.13	0.09	0.09	1.00
% In General Election	0.33	0.38	0.36	0.33	0.33	1.00
% Incumbent	0.00	0.12	0.00	0.00	0.00	1.00
Party						
% Republican	0.94	0.41	0.00	0.94	0.94	1.00
% Democrat	0.01	0.40	0.00	0.01	0.01	1.00
% Independent	0.03	0.08	0.01	0.03	0.03	1.00
% Other	0.02	0.11	0.00	0.02	0.02	1.00
Constituency						
% Open Seat	0.16	0.21	0.15	0.16	0.16	1.00
Population Density	2487.4	2303.8	0.00	2487.4	2503.4	1.00
Cook PVI (R)	-6.26	0.73	0.00	-6.26	-6.15	1.00
Median Age	38.77	38.66	0.39	38.77	38.78	0.99
% White	0.66	0.73	0.00	0.66	0.66	0.86
% Black	0.15	0.12	0.05	0.15	0.15	1.00
% Some College	0.62	0.62	0.53	0.62	0.62	1.00
Median Household Income ($1000s)	69.14	68.34	0.34	69.14	69.21	0.80

domly sampled 300 articles and assigned an independent research assistant to determine whether those articles referenced the candidate using a negative or non-negative tone.[4] We asked another independent RA to validate a subsample of these codings and we found that the research assistants chose the same coding label 86% of the time.[5] Table A1 shows example statements from news articles that the research assistants coded as negative (and non-negative) for both QAnon-supporting and non-supporting candidates in our dataset.

Recognizing that many of these articles were not solely about the referenced candidate, we split each article into paragraphs and kept any paragraph referencing the candidate, as well as the preceding and succeeding paragraphs for context.[6]

We set aside 40 labeled articles—10 from each possible combination of QAnon support and tone—as our test set, and we used the remaining text as a training set. We then trained several candidate models—including SVM, Boosted Logit, Random Forest, *k*-nearest neighbor, and penalized regression—to predict the sentiment of the unlabeled data using the `caretEnsemble` package in `R` (Deane-Mayer and Knowles 2019). The ensemble model's weighted in-sample accuracy was 0.88, and 0.75 out-of-sample.[7] We used this ensemble model to predict the tone of the remaining unlabeled newspaper articles.[8] The results of our text analysis resulted in a sample of 1,203 non-negative and 43 negative articles among non-supporters and 375 negative and 397 non-negative articles among QAnon-supporters.

Results: QAnon-Supporting Candidates Receive More Negative Coverage

Overall, the mean number of articles-per-candidate in our dataset is 7.3, but because a small number of candidates received extensive news coverage, the mean is highly skewed.[9] We find that 50 QAnon-supporting and 84 non-supporting candidates received coverage during the sample period. To determine whether QAnon-supporting candidates

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used by researchers, it can over-represent national news sources, which might lead us to underestimate candidates' overall media coverage. The matching procedure used should ensure that media coverage of both QAnon-supporting and non-supporting candidates are equally underestimated.

[4]Due to our multi-wave sampling procedure, some of the candidates included in the training data did not appear in the final sample of candidates.

[5]Please see Appendix A.2 for details on the coding instructions.

[6]To preprocess the text, we created a document frequency matrix of unigrams after removing stop words, symbols, numbers, separators, and punctuation; stemming words; removing words with two or fewer characters as well as those that appeared fewer than 5 times across all documents. We also removed the following words from all documents: QAnon, conspiracy, theory, theorist, theories, and Trump, which we suspected could bias our algorithm toward over-predicting negative articles among QAnon supporters and under-predicting among non-supporters. We weighted our document term matrix by term frequency–inverse document frequency.

[7]When the model misclassified articles out-of-sample, the direction of the error was biased toward coding true negatives as positive. Therefore, we expect any systematic bias in the predictions to be biased against our hypothesis.

[8]We train the same ensemble model and present results using only the smaller subsample of articles which both research assistants coded, excluding all articles on which they disagreed. We arrive at substantively similar conclusions as shown in Table A4.

[9]For example, QAnon-supporter Marjorie Taylor Greene and a non-supporting candidate, Carlos Giménez, received hundreds of articles each.

received more news coverage, we regress the total number of articles each candidate received on a binary indicator for QAnon support, accounting for the genetic matching weights, using a negative binomial regression. We use HC3 robust standard errors due to matching with replacement (Hill and Reiter 2006). We present these results in Table A3. The coefficient from this model is -0.20, a decrease of 1.74 articles on average, for supporting candidates—contrary to our hypothesis. However this difference is not statistically different from 0.[10] Ultimately, we find no evidence that QAnon-supporting candidates receive any more coverage than their non-supporting twins, meaning that we do not find evidence in support of our expectations.

Table A3: Effect of QAnon support on the number of news articles and number of negative articles.

	News Coverage	
	Total Number of Articles	Number Negative
Estimated ATT	-0.20	2.82^{***}
	(0.71)	(0.74)
T-Statistic	-0.28	3.82
p-value	0.78	0.00
No. Treated	96	96
No. Control (Unweighted)	168	168

Note: Estimated average treatment effect on the treated of QAnon support. The dependent variable in column 1 is the number of news articles referencing the candidate among the matched sample, and in column 2, the number of negative news articles referencing the candidate. Coefficients are from a negative binomial model with HC3 robust standard errors.

Next, we estimate a similar model where the dependent variable is the number of negative articles each candidate receives. Here we find a statistically significant and positive increase in negative articles as a result of QAnon support. The coefficient on treatment is 2.82, which equates to a 3.67 negative article increase on the original scale. These differences are statistically distinguishable at the 95% level, meaning that we find evidence to support our expectations. We find similar results in Table A4 with the smaller, double-coded sub-sample.

[10] In the analysis step, we discovered one miscoded non-supporting candidate in our matched sample, a sitting member of the House running for Senate. This candidate had a larger number of articles than other non-supporters. Nonetheless, their inclusion should bias against our hypotheses as they inflate the number of articles written about non-supporting candidates and also present more opportunities for negative coverage.

Table A4: Effect of QAnon support on the number of news articles and proportion of negative news coverage using smaller subsample with both RA codes.

	News Coverage	
	Total Number of Articles	Number Negative
Estimated ATT	-0.20	2.98^{***}
	(0.71)	(0.78)
T-Statistic	-0.28	3.82
p-value	0.78	0.00
No. Treated	96	96
No. Control (Unweighted)	168	168

Note: Estimated average treatment effect on the treated of QAnon support. The dependent variable in column 1 is the number of news articles referencing the candidate among the matched subsample, and in column 2, the number of negative news articles referencing the candidate. Coefficients are from a negative binomial model with HC3 robust standard errors.

Candidates who support the QAnon conspiracy theory receive the same amount of coverage as their non-supporting counterparts, on average. However, the tone of that coverage varies significantly. The coverage of the average QAnon-supporting candidate is roughly 3.67 articles more negative than the comparable candidate who never support QAnon. To the extent that these candidates are seeking negative coverage, supporting a trending conspiracy theory appears to do the trick.

B Experimental Evidence: News Tone and Candidate Favorability

Table B1: Balance statistics for experimental groups

	Neutral	Negative	QAnon	*F*-Statistic	*p*-Value
News Importance (5 point)	3.46	3.43	3.49	1.4	0.24
Party ID (7 Point)	3.85	3.72	3.86	1.5	0.22
Ideology (7 Point)	3.45	3.44	3.49	0.37	0.54
Female	0.5	0.54	0.5	1.44	0.23
Age (4 Point)	2.51	2.59	2.63	0.38	0.54
Education (5 Point)	3.16	3.03	2.95	1.27	0.26
Income (20 Point)	10.14	9.94	10.35	3.18	0.07
White	0.64	0.61	0.64	0.95	0.33
Black	0.09	0.12	0.12	0.15	0.70
Latin	0.18	0.2	0.15	6	0.01*
Asian	0.06	0.02	0.05	7.15	0.01*

B.1 Robustness Checks for Trust in Media, H1

In Table B2, we re-present results from the baseline model in the main text where we regress a respondent's evaluation of the candidate on a 101-point feeling thermometer on indicators for each treatment condition, trust in media, and their interactions. We also present three alternative specifications: one with controls and weights, wave 1 only, and wave 2 only. The coefficient sizes and their statistical significance are substantively similar across models.

Table B2: Robustness checks for the effects of treatment and trust in media on candidate favorability

	Candidate Thermometer Rating			
	Main Model	Controls and Weights	Wave 1	Wave 2
Trust in Media	2.81^{**}	4.61^{***}	3.19^{*}	1.02
	(1.01)	(1.07)	(1.39)	(1.51)
Negative	-5.17	-3.91	-7.19	-6.47
	(3.65)	(3.68)	(5.21)	(5.12)
QAnon	0.27	-2.62	1.24	-3.11
	(3.58)	(3.51)	(5.24)	(4.91)
Negative × Trust	-3.74^{**}	-4.26^{**}	-3.33	-2.69
	(1.42)	(1.43)	(1.98)	(2.04)
QAnon × Trust	-10.64^{***}	-9.21^{***}	-11.63^{***}	-8.48^{***}
	(1.40)	(1.37)	(1.98)	(1.99)
News Import		-1.38^{**}		
		(0.52)		
Party ID (7 Point)		0.71^{*}		
		(0.30)		
Ideology (7 Point)		1.42^{***}		
		(0.41)		
Female		2.54^{**}		
		(0.92)		
Age (4 Point)		-0.46		
		(0.44)		
Education (5 Point)		-0.46		
		(0.42)		
Income (20 Point)		-0.51^{***}		
		(0.12)		
White		1.66		
		(2.32)		
Black		4.12		
		(2.65)		
Latin		2.15		
		(2.49)		
Asian		8.46^{**}		
		(3.16)		
Baseline	49.33^{***}	46.33^{***}	51.34^{***}	50.46^{***}
	(2.58)	(4.30)	(3.70)	(3.64)
R^2	0.24	0.26	0.26	0.21
Adj. R^2	0.23	0.26	0.26	0.21
Num. obs.	1948	1931	973	975

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: Coefficients are all from ordinary least squares regressions where the dependent variable is a 101-point thermometer rating of the candidate.

B.2 Results for Party Identification, H2

In Figure B1, we present the marginal effects of each treatment comparison for each level of seven-point party identification. In contrast to our hypotheses, we find that Republicans *decrease* their evaluation of the candidate in the negative condition as compared to the control condition (H2a) as well as in the QAnon condition as compared to the control condition (H2b). Finally, we find no statistical difference between evaluations comparing the two treatments (H2c). We fail to support these three hypotheses.

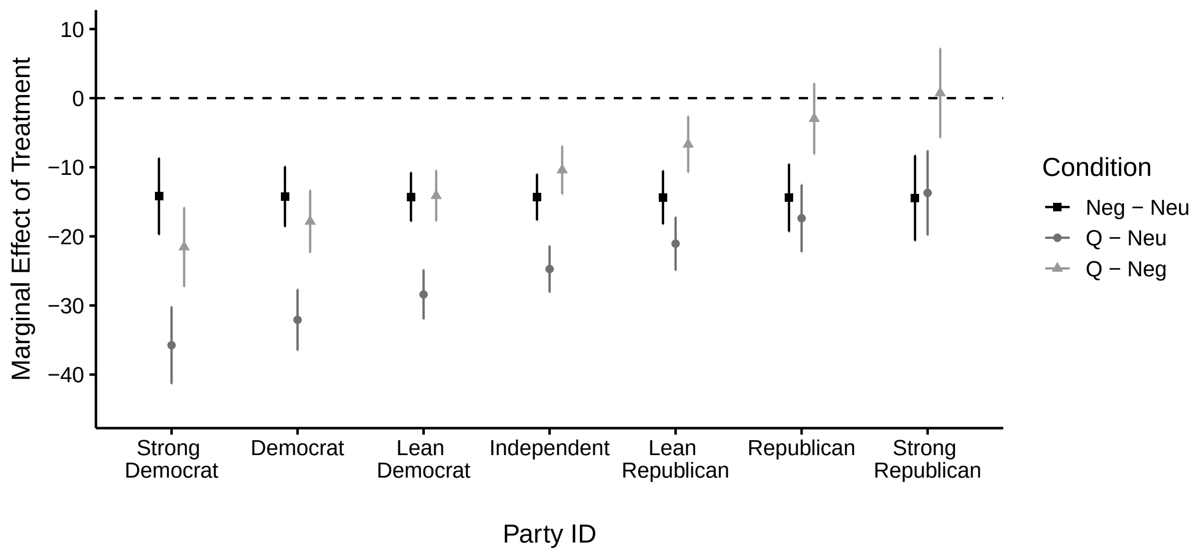

Figure B1: Average marginal effects of each treatment comparison for varying levels of party identification

In line with our hypotheses, we find that Democrats decrease their evaluations of the candidate in the negative condition as compared to the control condition (H2d), and even more so in the QAnon condition compared to the control condition (H2e). Finally, we find that these differences are statistically distinguishable from one another (H2f). We support all three of these hypotheses.

In Table B3, we present results from a model where we regress a respondent's evaluation of the candidate on a 101-point feeling thermometer on indicators for each treatment condition, seven-point party identification, and their interactions. We also present three alternative specifications: one with controls and weights, wave 1 only, and wave 2 only. The coefficient sizes and their statistical significance is substantively similar across models.

Table B3: Robustness checks for the effects of treatment and party ID on candidate favorability

	Candidate Thermometer Rating			
	Main Model	Controls and Weights	Wave 1	Wave 2
Party ID (7 Point)	-0.05	-0.63	0.13	-0.02
	(0.38)	(0.43)	(0.55)	(0.52)
Negative	-14.16^{***}	-16.27^{***}	-13.92^{***}	-13.90^{***}
	(2.30)	(2.35)	(3.31)	(3.18)
QAnon	-39.43^{***}	-39.35^{***}	-37.25^{***}	-40.39^{***}
	(2.32)	(2.36)	(3.35)	(3.18)
Negative $\times$ Party ID	-0.04	0.50	-0.48	0.24
	(0.54)	(0.54)	(0.80)	(0.72)
QAnon $\times$ Party ID	3.67^{***}	3.71^{***}	2.51^{**}	4.53^{***}
	(0.54)	(0.54)	(0.79)	(0.72)
Trust in Media (4 Point)		0.31		
		(0.66)		
News Importance (5 Point)		-1.27^{*}		
		(0.52)		
Ideology (7 Point)		1.54^{***}		
		(0.41)		
Female		2.53^{**}		
		(0.92)		
Age (4 Point)		-0.41		
		(0.44)		
Education (5 Point)		-0.59		
		(0.42)		
Income (20 Point)		-0.51^{***}		
		(0.12)		
White		1.72		
		(2.31)		
Black		4.45		
		(2.63)		
Latin		2.38		
		(2.48)		
Asian		9.28^{**}		
		(3.15)		
Baseline	56.32^{***}	61.23^{***}	58.94^{***}	52.90^{***}
	(1.66)	(4.07)	(2.34)	(2.33)
R^2	0.24	0.27	0.25	0.25
Adj. R^2	0.24	0.26	0.24	0.24
Num. obs.	1944	1931	969	975

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: Coefficients are all from ordinary least squares regressions where the dependent variable is a 101-point thermometer rating of the candidate.

B.3 Results for Name Recognition, H3

In Table B4, we present the results from two regressions where we regress a respondent's entry when asked to recall the candidate's name on the treatment indicators. Coefficients in column 1 are from an ordinary least squares regression and results in column 2 are from a logit regression. In column 1, the dependent variable is the Jaro Winkler string similarity score between the respondent's name recall answer and the candidate's name. In column 2, the dependent variable is a binary measure that takes on the value of 1 if the respondent entered the candidate's first or last name anywhere in their response, and 0 otherwise. We find no evidence that either treatment increased name recall, so we fail to support H3a-H3c.

Table B4: Regression results for candidate name recognition.

	Name Recognition	
	Jaro Winkler Score	Binary Measure
Negative	-0.01	-0.03
	(0.02)	(0.11)
QAnon	-0.02	-0.12
	(0.02)	(0.11)
Constant	0.63^{***}	0.07
	(0.01)	(0.08)
R^2	0.00	
Adj. R^2	0.00	
Num. obs.	1960	1960

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: Coefficients in column 1 are from an ordinary least squares regression and results in column 2 are from a logit regression. In column 1, the dependent variable is the Jaro Winkler string similarity score between the respondent's name recall and the candidate's name. In column 2, the dependent variable is a binary measure that takes on the value of 1 if the respondent entered the candidate's first or last name anywhere in their response, and 0 otherwise.

B.4 Results for Alternative Vignettes

In Figures B2 and B3, we present results from follow up vignette experiments conducted on Mechanical Turk in January of 2021. Our original vignettes depicted our candidate as having lost the race and they included several constituent quotes in the hypothetical articles describing the candidate. We believed these features could have depressed potential support for the candidate, which we tested in this follow up. In both follow ups, we described the candidate as having won the race. In one, we also removed the quotes to imply that it was the media, not constituents, who felt negatively toward the candidate. In both versions, we also randomly presented each respondent with one of several candidate names. The *QAnon* version of both alternative vignettes are presented in Table B5.

Table B5: Alternative Treatments

Treatment	**Text**
QAnon, Winner	**Statehouse Representative, QAnon Supporter, Wins Congressional Bid** John Smith, a two-term state representative, recently ran for an open seat in the House of Representatives. John Smith is a vocal supporter of the convoluted QAnon conspiracy theory. John Smith barely won his last election to the statehouse, but his latest bid for Congress has proven to be successful. He won the congressional election by a wide margin, even though his campaign was poorly organized. Constituents had bad feelings about the election outcome. One constituent tweeted "John Smith's bid for Congress was a joke. I can't believe he won." Another commented "John Smith ran a weak campaign and advanced a lot of terrible ideas for our district. I hope he never gets the chance to run again." He pledged to bring fresh ideas to Washington and ensure his constituents had their voices heard. Now he will have his chance.
QAnon, No Quotes	**Political Novice, QAnon Supporter, Wins Longshot House Race** John Smith, a political novice who has openly voiced his support for the baseless QAnon conspiracy theory, recently won an upset victory in November, unseating a two-term incumbent. Over the course of the campaign he had taken some extremely unpopular policy positions. Many were surprised by the result and remain concerned about how he will be as a representative now that he has won. "I ran because I want to fight for you in Washington," John Smith said in his victory speech. Nearly half of his constituents were not willing to believe him.

As in our original experiment, respondents were randomly shown one of three possible vignettes: *Neutral*, *Negative*, and *QAnon*, and we asked them to rate the candidate on a 101-point feeling thermometer. We regressed that outcome on an interaction between the treatment condition and pre-treatement trust in media as well as the constituent terms. In Figure B2, we display the marginal effects of the treatments for each level of trust in media for the condition with the winning candidate and quotes. The results in Figure B2 are similar to those in the main text. Regardless of one's trust in media, no one *increases* their support for the QAnon-supporting candidate.

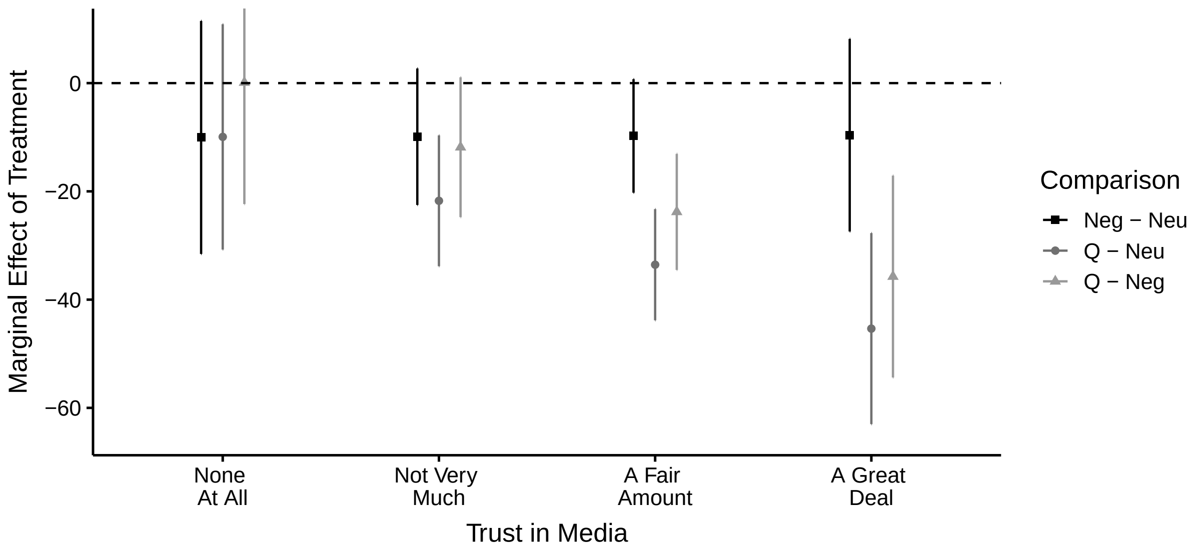

Figure B2: Average marginal effects of each treatment comparison at varying levels of trust in media when the candidate is described as having won his race.

We presented other respondents with a different vignette in which we described the candidate as having won, but we also removed the constituent quotes, allowing more negativity to come directly from the hypothetical reporter. Using the same specification as above, we compute and display the marginal effects in Figure B3. The results are again similar to those in the main text: QAnon-support does not cause any group of respondents to increase support for the candidate.

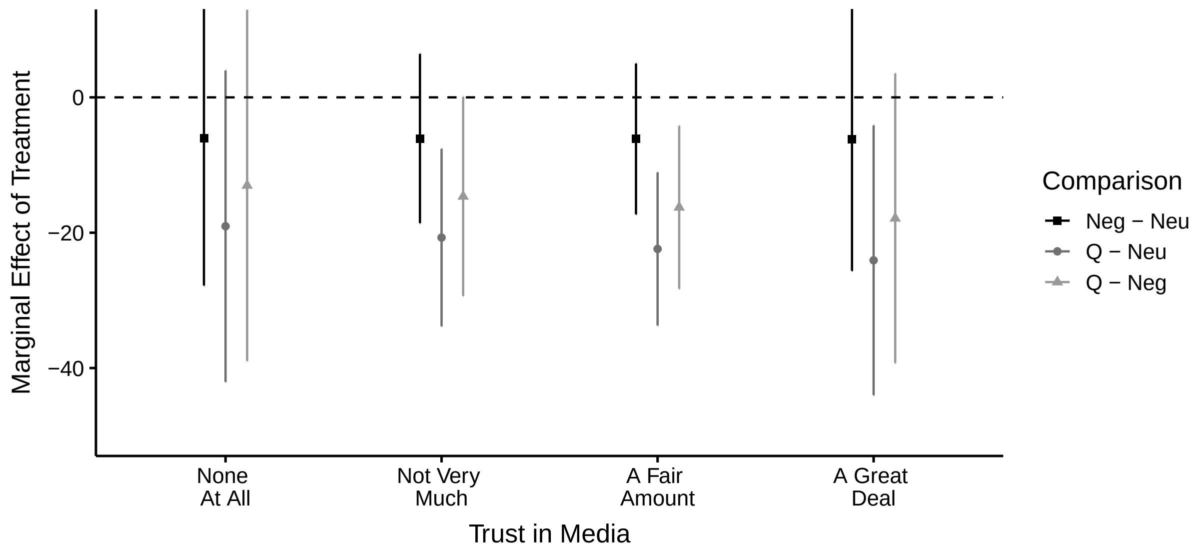

Figure B3: Average marginal effects of each treatment comparison at varying levels of trust in media when the candidate is described as having won his race and with constituent quotes removed.

C Experimental Evidence: Conjoint

Table C1: Conjoint sample demographics

	Sample Mean
Female	0.50
Average Age	37.65
Proportion Republican	0.49
Proportion Democrat	0.51
Proportion Independent	0.01
Proportion Employed	0.72

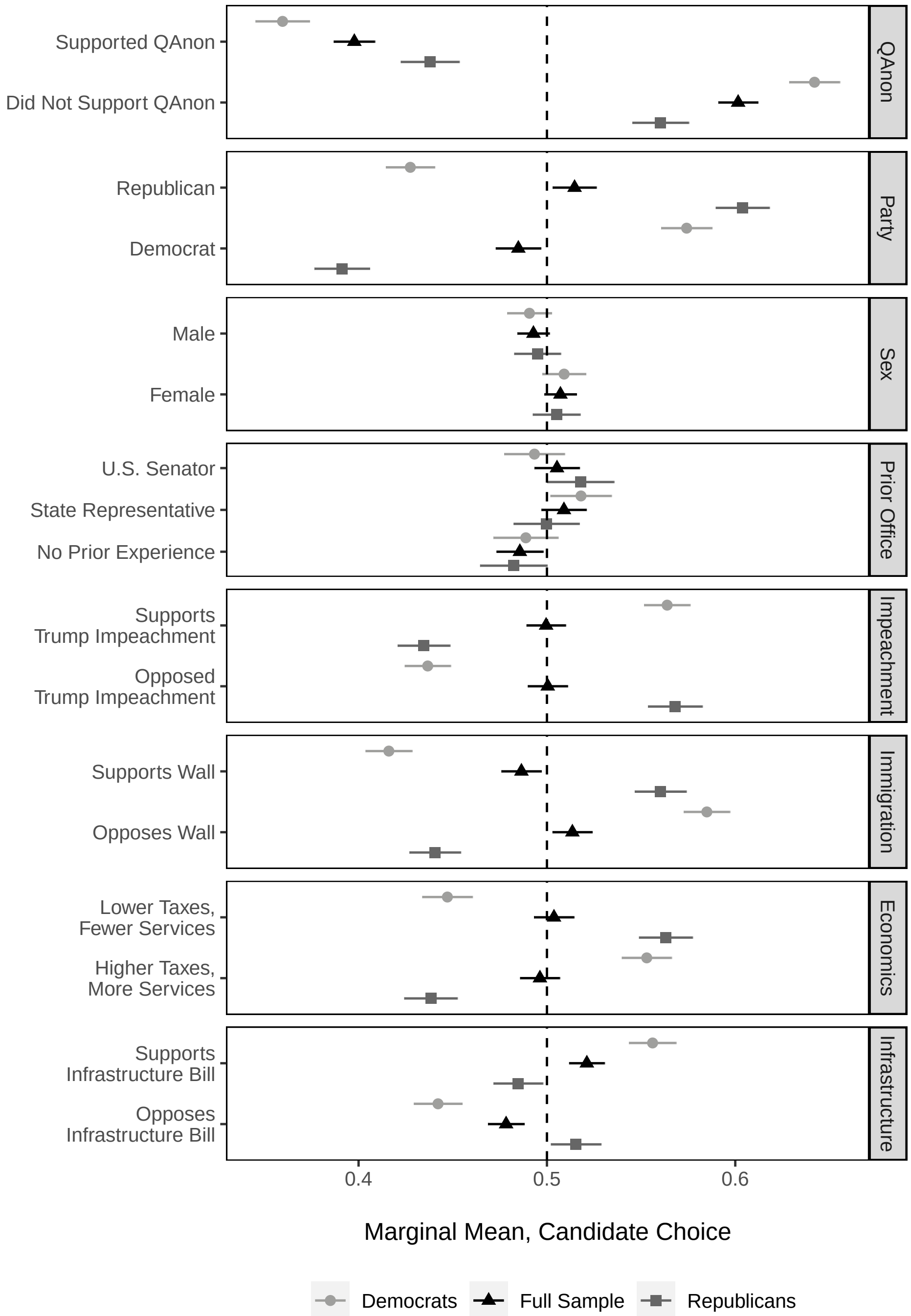

Figure C1: Marginal mean estimates of attributes on vote choice. QAnon support exerts a negative effect on Republican and Democratic vote choice.

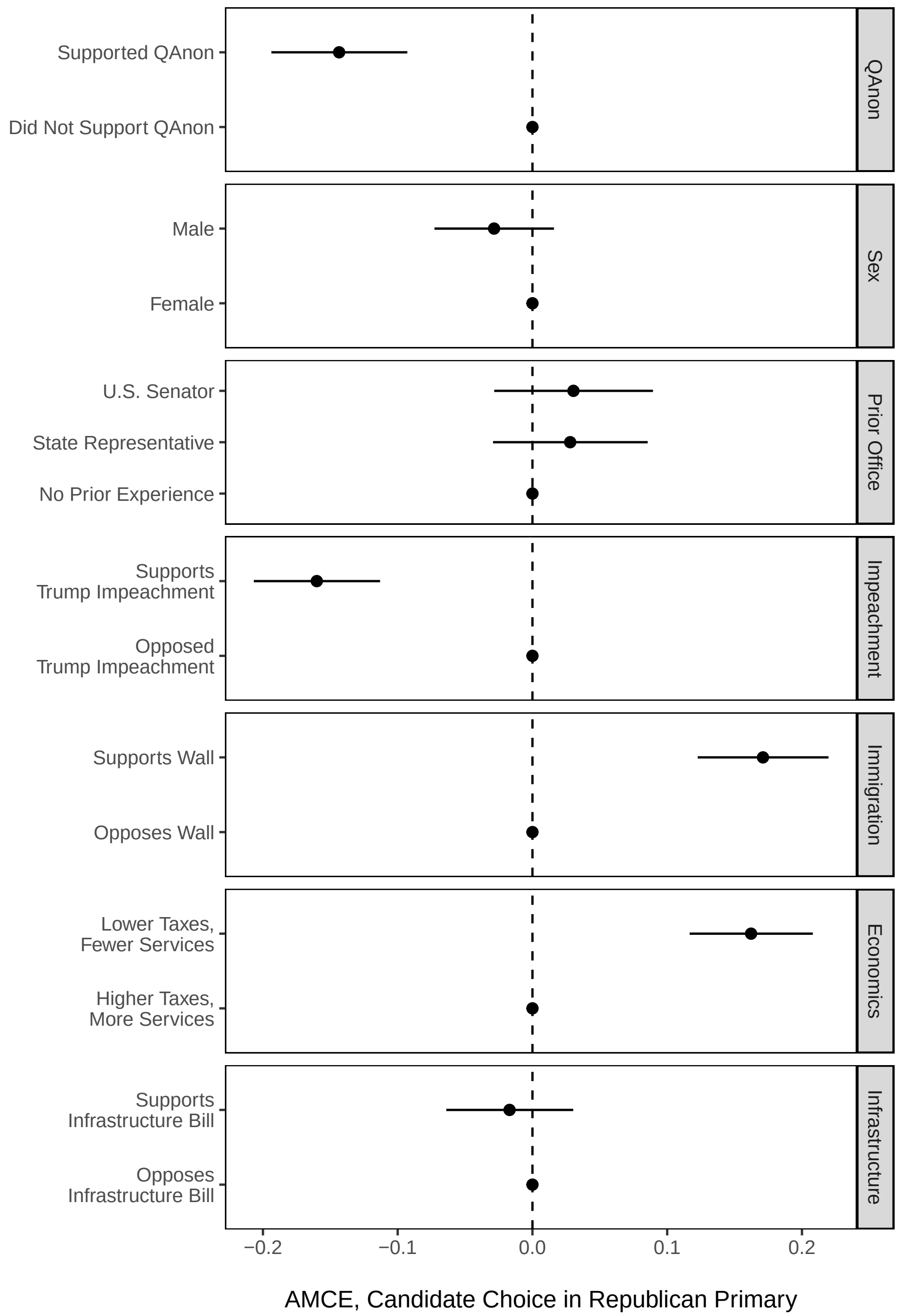

Figure C2: AMCE of each attribute on candidate choice in a Republican primary context. QAnon support causes a decline in vote choice. We include only choices between two Republican candidates and subset to just Republican respondents to estimate this model.

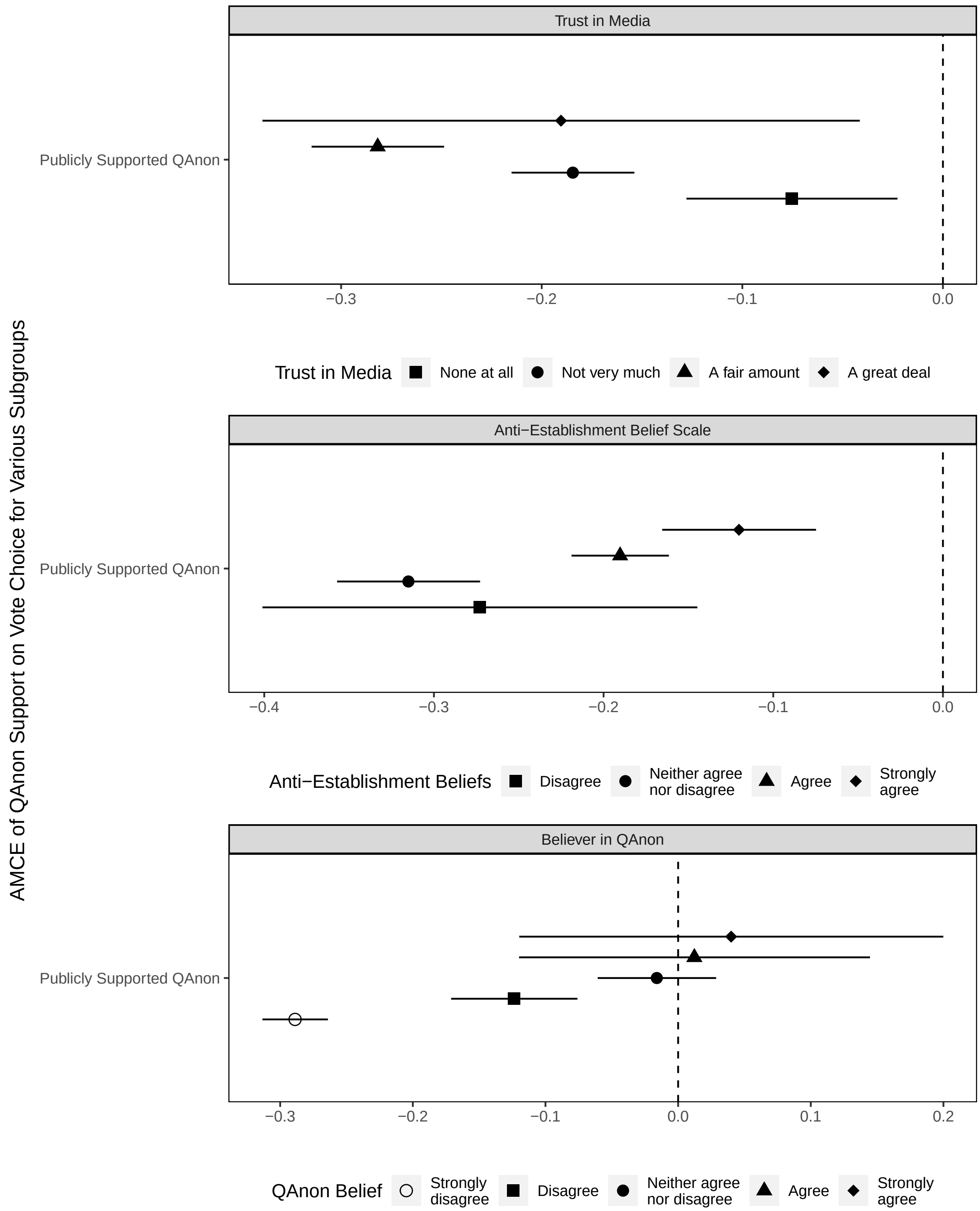

Figure C3: AMCE of QAnon support on candidate choice for each level of the moderator variable (as compared to no QAnon support). We round up values of the antiestablishment scale to the nearest whole value for tractability. Neither lower trust in media nor anti-establishment beliefs cause respondents to increase the probability of voting for a QAnon-supporting candidate. However, respondents who themselves believe QAnon are more likely to vote for a candidate who supports the conspiracy theory, but these results are not statistically significant given the small sample size.

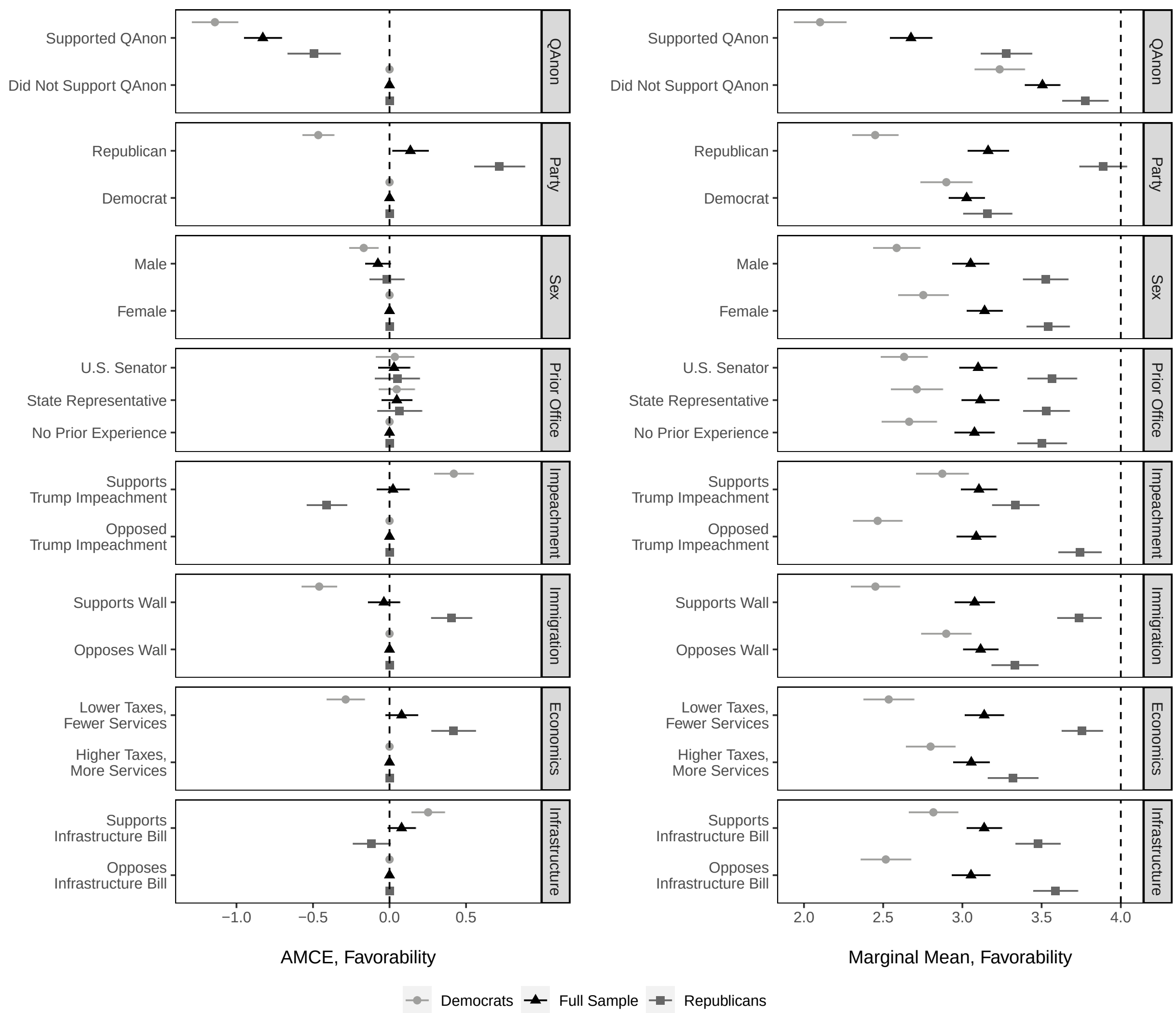

Figure C4: AMCE (left) and marginal means (right) of each attribute on 7-point favorability. QAnon support causes a decline in favorability, however, this effect is larger among Democrats than Republicans.

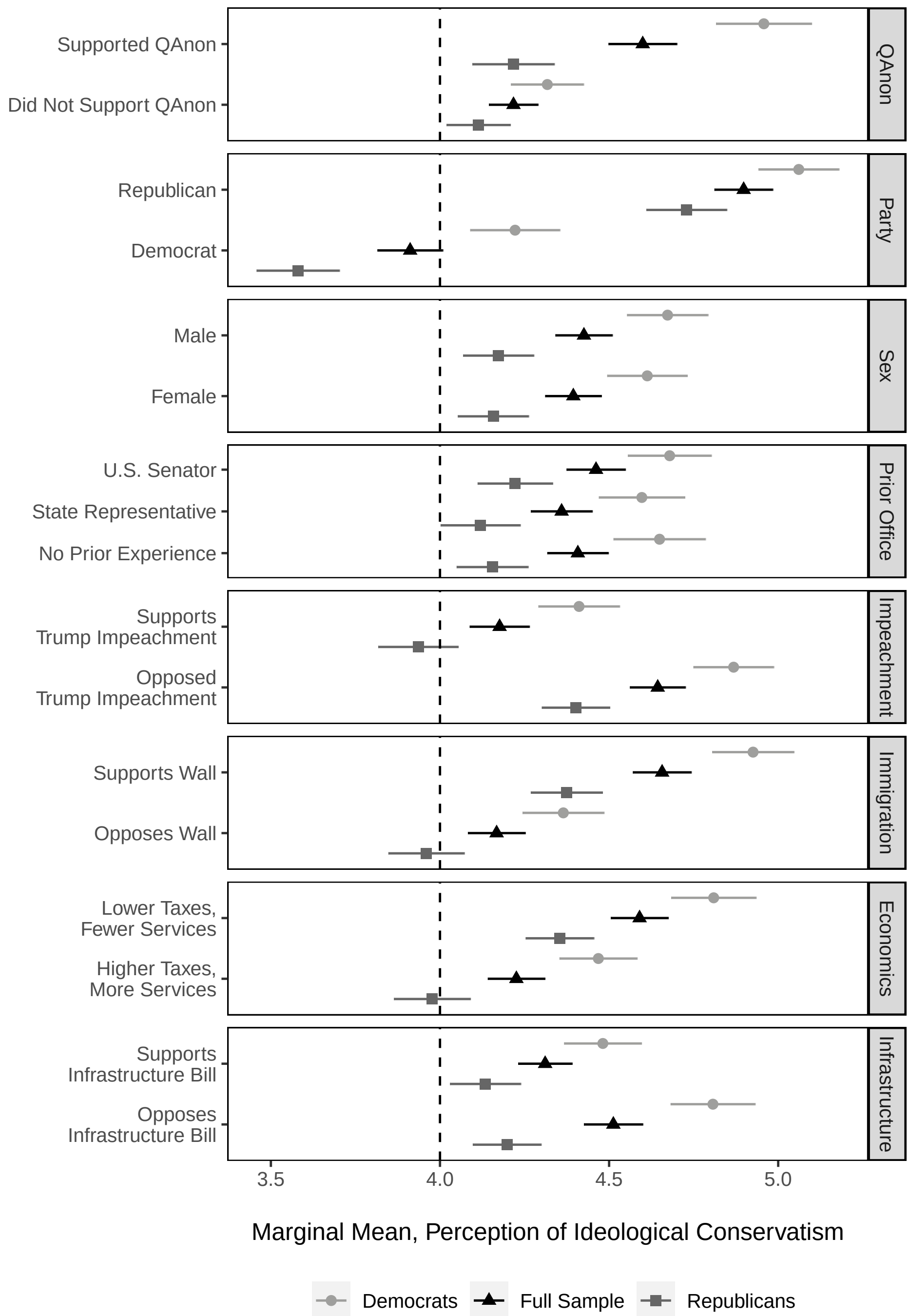

Figure C5: Marginal mean estimates of attributes on perceived ideology. QAnon support exerts a positive effect on Republican and Democratic perceptions.

References

Darr, Joshua P, Matthew P Hitt and Johanna L Dunaway. 2018. "Newspaper Closures Polarize Voting Behavior." *Journal of Communication* 68(6):1007–1028.

Deane-Mayer, Zachary A. and Jared E. Knowles. 2019. "caretEnsemble Package." *R Package* Version 2.0.1.

Diamond, Alexis and Jasjeet S. Sekhon. 2013. "Genetic Matching for Estimating Causal Effects: A General Multivariate Matching Method for Achieving Balance in Observational Studies." *Review of Economics and Statistics* 95(3):932–945.

Explorer, Social. N.d.
URL: *https://www.socialexplorer.com/*

Hill, Jennifer and Jerome P. Reiter. 2006. "Interval estimation for treatment effects using propensity score matching." *Statistics in Medicine* 25(13):2230–2256.

Kaplan, Alex. 2020. "Here are the QAnon supporters running for Congress in 2020.".
URL: *https://www.mediamatters.org/qanon-conspiracy-theory/here-are-qanon-supporters-running-congress-2020*