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 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 advanced to the general election, 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 A1. 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 A1, we present covariate balance and p-values from t-tests and bootstrapped Kolmogorov-Smirnov tests. The smallest p-value is 0.78, indicating that the distribution of each covariate is statistically similar between groups.

After creating this matched subset, we collected all English-language 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—international, 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

[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] 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.

Table A1: Matching Balance

	Before Matching			After Matching		
	QAnon Supporter	Non-Supporter		QAnon Supporter	Non-Supporter	
	mean	mean	p-value	mean	mean	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	1.00
% White	0.66	0.73	0.00	0.66	0.66	0.82
% 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	69.20	0.78

Note: p-values are from t-tests for binary variables and boostraped KS tests for continuous variables.

Guardian, as well as local sources like *Alaska Dispatch News* (AK) and the *Pueblo Chiefton* (CO).[3] From this large set, we randomly 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 A2 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]

[3]Our media corpus does not include TV-first (e.g., Fox, MSNBC, CNN) or blog-style (e.g., Breitbart, Daily Beast) media. Thus, our sample is biased toward mainstream news, which may lean left. Even so, we argue that this sample restriction likely underestimates both the amount and negativity of QAnon coverage. Although we exclude conservative sources like Fox News and Breitbart, we also exclude liberal sources like MSNBC. Indeed, we conducted a brief search of the TV News Archive on archive.org and found that, during our coverage period, MSNBC referenced QAnon in 220 clips as compared to Fox News' 26 references. Thus, including mainstream TV would likely tilt the balance in favor of our original hypotheses. Further, a vanishingly small proportion of the population consumes news from sources like Breitbart and One America News (OAN). A 2021 Pew study asked respondents to "click on all of the sources that you got political news from in the past week." Just 4% chose Brietbart and 7% chose OAN as compared to 26% for the New York Times and 23% for the Washington Post (Shearer and Mitchell 2021). Even if these right-wing sources talk frequently and positively about QAnon, the proportion of Americans consuming that content (as compared to content in our corpus of media coverage) is likely insufficient to shape electoral outcomes. Although the question of what conservative outlets are saying about conspiracy theories, and how that shapes candidate evaluations, is an important question in its own right, it is not the core focus our study.

[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]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.

Table A2: 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.

The results of our text analysis resulted in a sample of 1,188 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 7.6, but because a small number of candidates received extensive news coverage, the mean is highly skewed.[9] We find that 50 QAnon-supporting and 81 non-supporting candidates received coverage during the sample period. To determine whether QAnon-supporting candidates 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

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

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.

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 counterparts, meaning that we do not find evidence in support of our expectations.

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 number of negative articles 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.

B Vignette Experiment: News Tone and Candidate Favorability

Table B1: Balance statistics for experimental groups.

Variable	Neutral	Negative	Conspiracy	*F*-Stat	*p*-Value
News Importance (5 point)	3.46	3.43	3.49	1.40	0.24
Party ID (7 Point)	3.85	3.72	3.86	1.50	0.22
Ideology (5 Point)	3.00	3.02	3.08	1.18	0.28
Female	0.50	0.54	0.50	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	0.20	0.15	6.00	0.01*
Asian	0.06	0.02	0.05	7.15	0.01*
Metro	0.84	0.84	0.83	0.15	0.70

B.1 Robustness Checks for Trust in Media, H1

In Table B2, we re-present results from the baseline model in the main text. 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	2.40*	4.39***	3.19*	1.02
	(1.01)	(1.08)	(1.39)	(1.51)
Negative	−6.26+	−5.22	−7.19	−6.47
	(3.64)	(3.71)	(5.21)	(5.12)
QAnon	−0.33	−2.52	1.24	−3.11
	(3.56)	(3.51)	(5.24)	(4.91)
Negative x Trust	−3.30*	−3.84**	−3.33+	−2.69
	(1.41)	(1.44)	(1.98)	(2.04)
QAnon x Trust	−10.37***	−9.24***	−11.63***	−8.48***
	(1.39)	(1.37)	(1.98)	(1.99)
Wave	−4.28***	−3.78***		
	(0.91)	(0.91)		
News Importance		−1.40**		
		(0.52)		
Party ID (7)		0.69*		
		(0.32)		
Ideology (5)		1.44**		
		(0.53)		
Female		2.42**		
		(0.92)		
Age (4)		−0.35		
		(0.44)		
Education (5)		−0.33		
		(0.43)		
Income (18)		−0.55***		
		(0.12)		
White		2.29		
		(2.34)		
Black		4.94+		
		(2.66)		
Latin		2.91		
		(2.51)		
Asian		9.49**		
		(3.17)		
Baseline	56.74***	52.37***	51.34***	50.46***
	(3.01)	(4.68)	(3.70)	(3.64)
Num.Obs.	1948	1909	973	975
R2	0.244	0.272	0.262	0.213
R2 Adj.	0.242	0.266	0.259	0.208

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

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 as well as in the QAnon condition as compared to the control condition. Finally, we find no statistical difference between evaluations comparing the two treatments. We fail to support these three hypotheses.

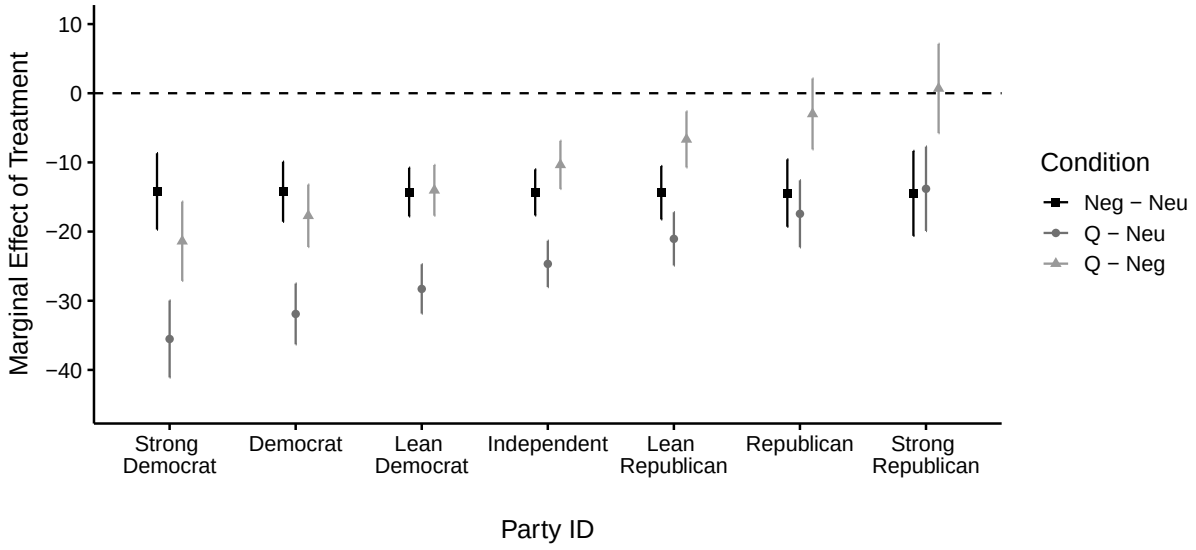

Figure B1: Average marginal effects of each treatment comparison for varying levels of party identification. Confidence intervals are the 0.998 level.

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 the model used to generate the figure above. 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)	0.02	−0.61	0.13	−0.02
	(0.38)	(0.45)	(0.55)	(0.52)
Negative	−14.14***	−16.13***	−13.92***	−13.90***
	(2.29)	(2.35)	(3.31)	(3.18)
QAnon	−39.15***	−39.36***	−37.25***	−40.39***
	(2.31)	(2.35)	(3.35)	(3.18)
Negative x Party ID	−0.05	0.39	−0.48	0.24
	(0.53)	(0.54)	(0.80)	(0.72)
QAnon x Party ID	3.62***	3.71***	2.51**	4.53***
	(0.53)	(0.54)	(0.79)	(0.72)
Wave	−4.20***	−3.99***		
	(0.90)	(0.90)		
News Importance		−1.28*		
		(0.52)		
Trust in Media		0.19		
		(0.67)		
Ideology (5)		1.57**		
		(0.53)		
Female		2.42**		
		(0.92)		
Age (4)		−0.30		
		(0.44)		
Education (5)		−0.47		
		(0.42)		
Income (18)		−0.55***		
		(0.12)		
White		2.46		
		(2.33)		
Black		5.39*		
		(2.65)		
Latin		3.21		
		(2.50)		
Asian		10.42***		
		(3.16)		
Baseline	62.36***	67.14***	58.94***	52.90***
	(2.10)	(4.39)	(2.34)	(2.33)
Num.Obs.	1944	1909	969	975
R2	0.250	0.277	0.248	0.246
R2 Adj.	0.248	0.270	0.245	0.242

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

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 and wave indicators. Coefficients in columns 1 and 2 are from an ordinary least squares regressions and results in column 3 are from a logit regression. In columns 1 and 2, the dependent variable is the Jaro Winkler string similarity score between the respondent's name recall

answer and the candidate's name. In column 3, 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 H3.

Table B4: Regression results for candidate name recognition.

	Name Recognition			
	Jaro Winkler Score			Binary Measure
Negative	−0.01	−0.01	−0.01	−0.04
	(0.02)	(0.01)	(0.01)	(0.12)
QAnon	−0.02	−0.02	−0.01	−0.11
	(0.02)	(0.01)	(0.01)	(0.12)
Wave		−0.12***	−0.12***	−1.40***
		(0.01)	(0.01)	(0.10)
News Importance			0.02**	
			(0.01)	
Ideology (7)			0.00	
			(0.01)	
Female			0.01	
			(0.01)	
Age (4)			−0.03***	
			(0.01)	
Education (5)			0.02**	
			(0.01)	
Income (18)			0.00	
			(0.00)	
White			−0.04	
			(0.03)	
Black			−0.13***	
			(0.03)	
Latin			−0.05	
			(0.03)	
Asian			−0.03	
			(0.04)	
Baseline	0.63***	0.81***	0.79***	2.18***
	(0.01)	(0.02)	(0.05)	(0.17)
Num.Obs.	1960	1960	1920	1960
R2	0.001	0.050	0.085	
R2 Adj.	0.000	0.049	0.079	

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

Note: Coefficients in columns 1 and 2 are from an ordinary least squares regression and results in column 3 are from a logit regression. In columns 1 and 2, the dependent variable is the Jaro Winkler string similarity score between the respondent's name recall and the candidate's name. In column 3, 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 Perceived Ideology

In Table B5, we use Wave 2 data to investigate the effects of the treatments on perceptions that the candidate is ideologically conservative. These models are used to produce Figure 2 in the main text.

Table B5: Media coverage describing candidates as supporting QAnon causes respondents to believe they are more ideologically conservative

	All Respondents	Republicans	Low Trust in Media
Negative	0.10	0.38**	0.06
	(0.10)	(0.13)	(0.15)
QAnon	1.04***	1.49***	1.30***
	(0.10)	(0.13)	(0.15)
Low Trust in Media			−0.09
			(0.15)
Republican		0.19	
		(0.15)	
Negative x Republican		−0.69***	
		(0.21)	
Negative x Low Trust in Media			0.08
			(0.21)
QAnon x Republican		−1.15***	
		(0.21)	
QAnon x Low Trust in Media			−0.52*
			(0.21)
Baseline	4.06***	3.98***	4.11***
	(0.08)	(0.10)	(0.12)
Num.Obs.	977	974	974
R2	0.112	0.161	0.128
R2 Adj.	0.110	0.157	0.124

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

Note: Coefficients are from ordinary least squares models where the dependent variable is perceived ideology of the candidate on a 7-point scale where higher values are more conservative. Model 1 is among the full sample. Model 2 interacts treatment with Republicans versus Democrats/Independents. Model 3 interacts treatment with a low (1 or 2) versus high (3 or 4) self-reported trust in media.

B.5 Results for Robustness Tests

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 B6.

Table B6: 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

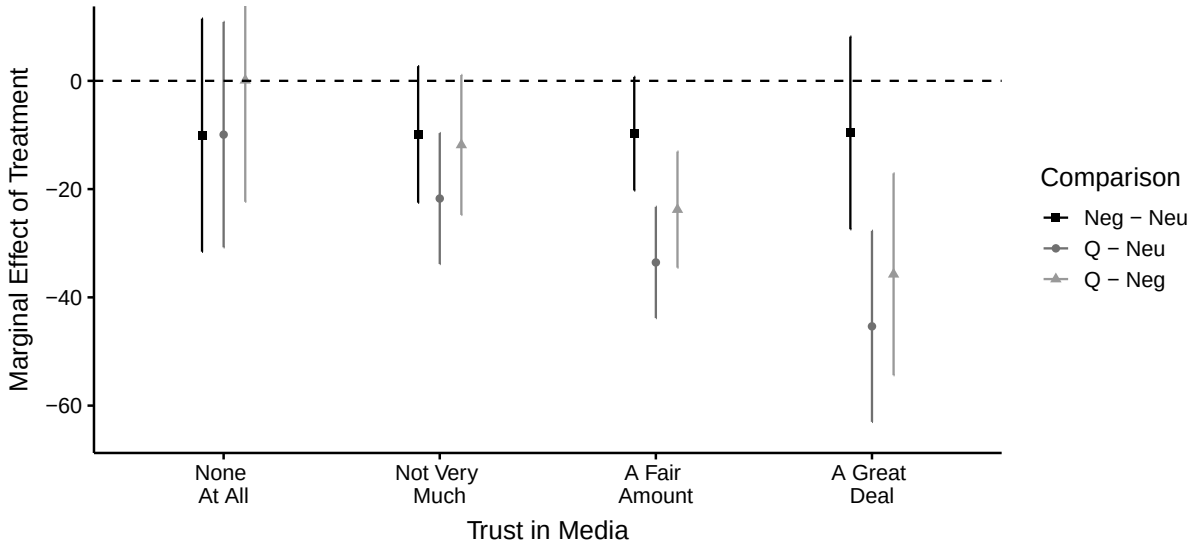

Figure B2: Average marginal effects of each treatment comparison at varying levels of trust in media when the candidate is described as having won his race. Confidence intervals are at the 0.996 level.

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.

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.

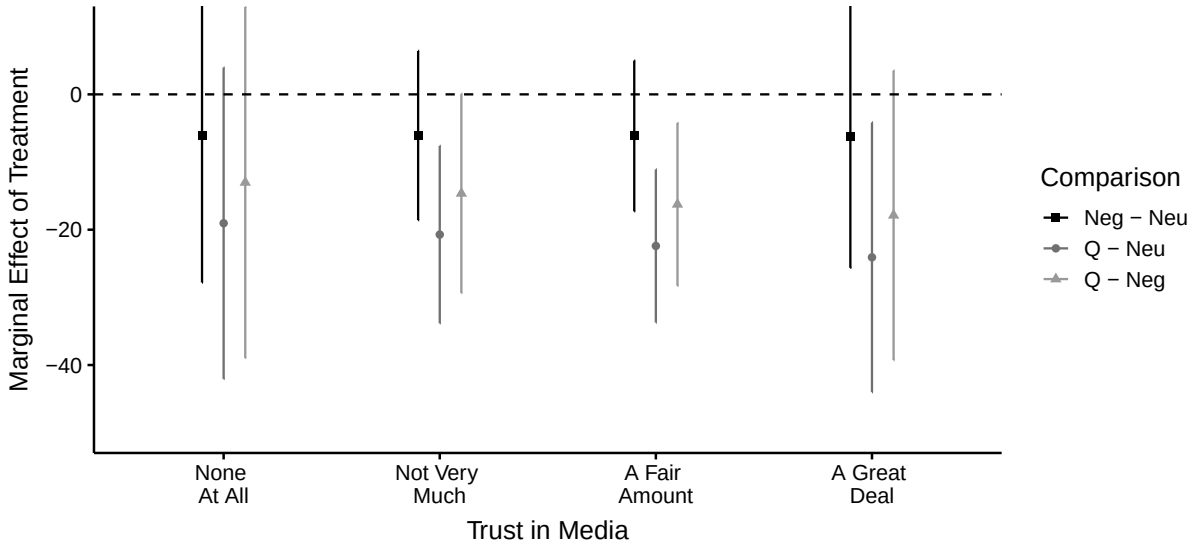

Figure B3: Average marginal effects of each treatment comparison at varying levels of trust in media when the candidate is described as having won his race and with constituent quotes removed. Confidence intervals are at the 0.996 level.

In our observational analysis, we find that QAnon-supporting candidates disproportionately run for House, rather than Senate, seats. Accordingly, there is a possibility that in rural House districts, support for QAnon-endorsing candidates is stronger—something we may not be able to detect in the full analysis of our nationally representative survey. Our two-wave survey experiment does include a dummy variable that accounts for whether an individual resides in a metropolitan area (`metro = 1`) or not (`metro = 0`).

To test this possibility, we interact our metro indicator with the treatment and include constituent terms. We then plot the marginal effect of QAnon support versus negative coverage in Figure B4. We see that while non-metro respondents are marginally more supportive of QAnon-supporting candidates than metro respondents, they still penalize this candidate. However, we urge caution in over-interpreting these results—although this variable is balanced across treatment groups, our sample contains only 316 non-metro respondents. Acknowledging that our sample of non-metro respondents is quite small, and perhaps not broadly representative of type of rural respondents who would support such a candidate, these results do not point toward any substantive differential attitudes toward QAnon-supporting candidates. Future work could consider a rural over-sample to better test these possibilities.

Another possibility for our counter-intuitive findings is that people who distrust media are broadly distrusting and are simply not inclined to rate *any* politician favorably. To investigate this proposal, we leverage a pre-treatment question in Wave 2 of our survey that specifically asks respondents "In general, how much trust and confidence do you have in Fox News when it comes to reporting the news fully, accurately, and fairly?" Respondents answer on a four-point scale, where higher values indicate more trust and

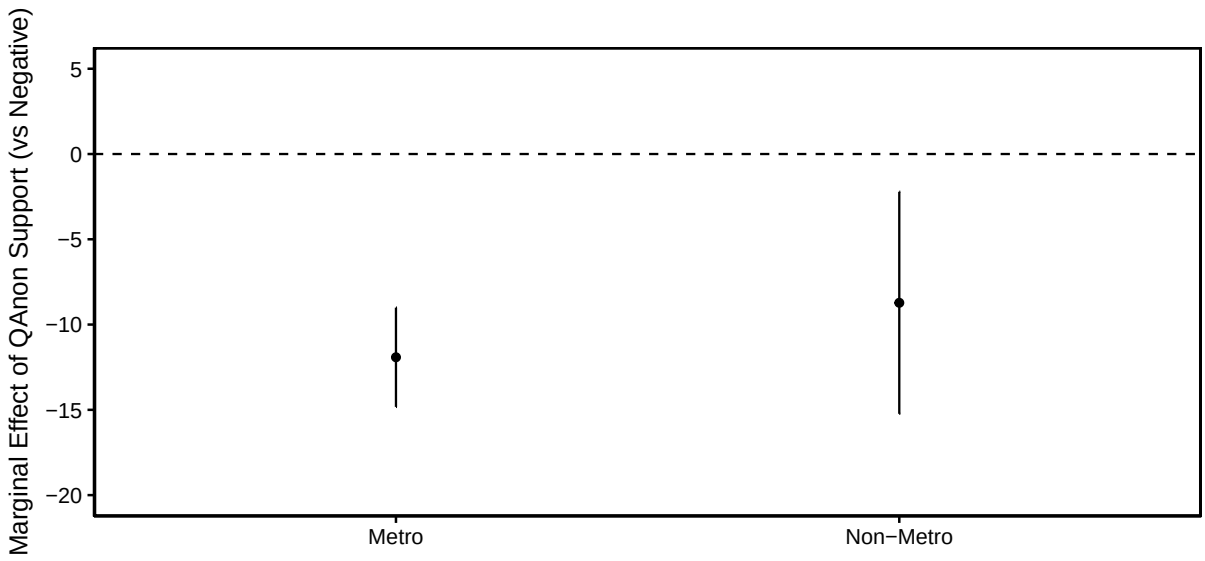

Figure B4: Average marginal effects of candidate QAnon support (versus negative coverage) for those who live in metro or non-metro areas. Confidence intervals are at the 0.975 level.

support in Fox News. This question is helpful in this context because (i) people who watch Fox News should be more likely to approve of QAnon-supporting candidates and (ii) given their approval of Fox News, we can conclude that they do not simply distrust and oppose *all* political objects. Trust in Fox News is negatively correlated with general trust in media (-0.2) as expected. As such, some individuals who distrust media are nonetheless supportive of Fox News, indicating they do not hold globally negative attitudes toward politics.

We regress the candidate thermometer rating on both treatments, Fox News trust, and the interactions. The key quantity of interest is the marginal effect of the QAnon treatment at each level of Fox News support for the various treatment comparisons, which can be found in Figure B5. We adjust confidence intervals for multiple comparisons as in the main text. Although there does not appear to be an effect of just negative coverage, those who are more trusting of Fox News are more approving of QAnon-supporting candidates than those who do not trust Fox News. As compared to the neutral candidate, the marginal effect of QAnon support is negative, but not statistically different from 0. However, comparing a candidate who is covered negatively to one covered negatively who supports QAnon, favorablilty actually increases by 9 points. Again, this is not statistically different from 0, but is suggestive of increasing support. This result cuts against the general idea of a group of people who will never support any candidate. It also does not support the idea of a general preference for QAnon-supporting candidates. However, among those who most trust Fox News, there could be some benefit for candidates supporting QAnon if they would otherwise be covered negatively. Further, we fail to

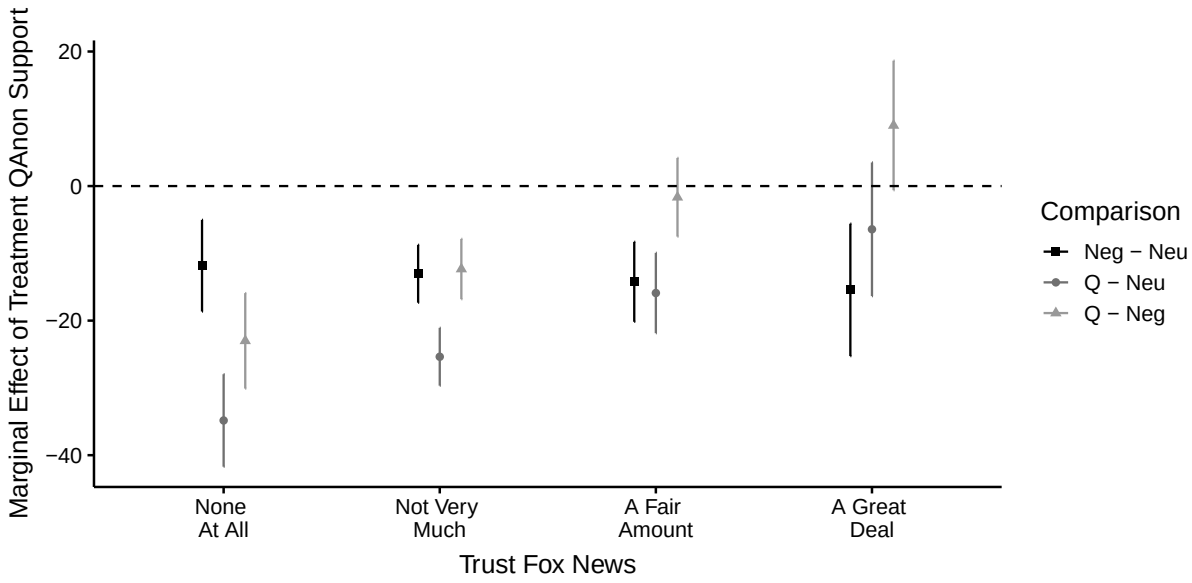

Figure B5: Average marginal effects of candidate QAnon support at varying levels of trust in Fox News. Confidence intervals are at the 0.995 level

replicate this effect in our conjoint experiment (see Figure C3). There, those who report engaging with Fox News "several times" or "every day" exact a small, but statistically significant penalty on these candidates as compared to similar candidates who did not support QAnon.

Although we find that those with low trust in media penalize QAnon-supporting candidates, there are factors beyond trust in media that could moderate the effect. In particular, older individuals or those who identify as evangelical or religious might be favorable toward QAnon-supporting candidates; these groups may be large and supportive enough to offset other penalties we observe. To investigate this possibility, we focus on just candidates in the negative and QAnon treatment groups (a harder test). We regress the candidate thermometer rating on the QAnon treatment indicator and interact it with (1) a four-point age variable, (2) evangelical identification from wave 2,[11] and (3) a nine-point religious attendance variable from wave 1. Figure B6 shows that none of these groups increase support for QAnon-supporting candidates as compared to candidates who are covered negatively but did not support QAnon.

Another potential concern regards demand effects stemming from lack of knowledge about QAnon. That is, if a respondent doesn't know much about the conspiracy theory or about politics in general, they may have a vague sense that it is "bad" and therefore, they infer that they should rate these candidates negatively. First, our follow-up conjoint should rule out this possibility to some extent. The virtue of the conjoint is in obfuscating the QAnon attribute among several other (un)attractive features of a candidate. If

[11]This question was asked post-treatment, however, it seems unlikely our treatment would lead to a large bias in religious identification.

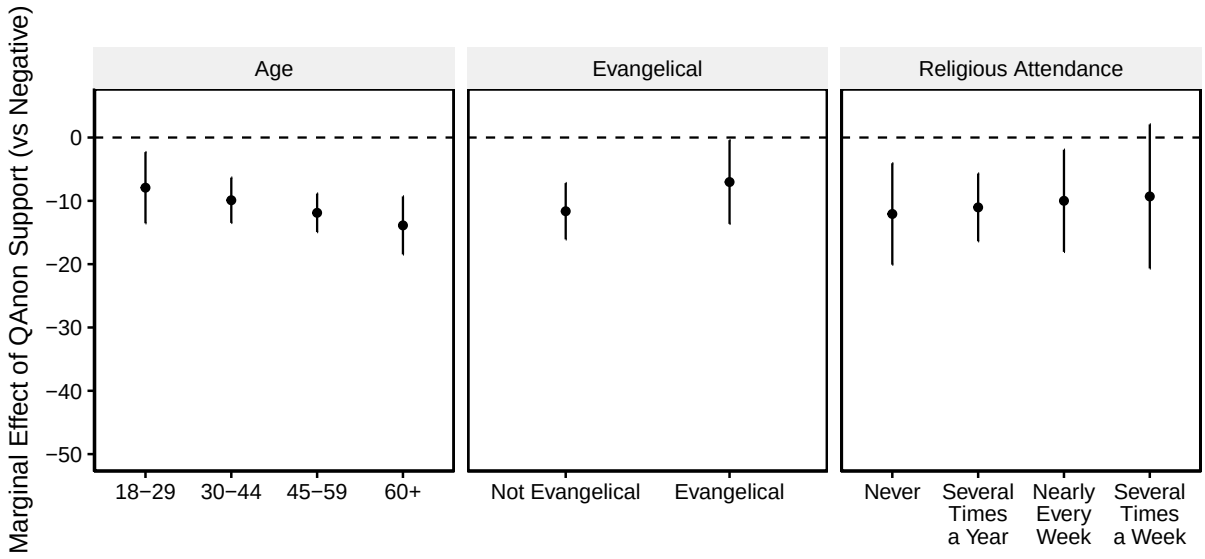

Figure B6: Average marginal effects of candidate QAnon support at varying levels of age, evangelical identification, and religious attendance (only select levels shown for presentation) versus negative coverage. Confidence intervals are at the 0.988, 0.975, and 0.994 level moving from left to right.

people know little about QAnon, we would expect to see them latch on to other, simpler heuristics (such as a party ID) to make their choice and ignore this attribute. Yet, we find consistent penalties exacted on this candidate even in this setting, which we would expect to be more difficult as compared to our vignette which is potentially more overt in broadcasting researcher intent.

However, we have some data that would allow us to directly test the hypothesis that those with low knowledge of QAnon, or politics generally, are more likely to penalize these candidates, whereas those with more knowledge would not. In particular, our survey included a question where we asked respondents "Based on what you have heard or read, would you say you have a positive impression of QAnon, a negative impression of QAnon, or don't you know enough to say?" We also asked respondents "How important is it to you personally to keep up with news and information?" and provided a five-point scale where higher values were associated with more importance.

We regress the candidate feeling thermometer in our vignette experiment on the treatment indicators, each of these variables, and their interactions in two separate models. We produce marginal effects plots to interpret substantive effect sizes in Figure B7, focusing on the negative vs QAnon comparison, the harder test. We also follow our other figures and correct confidence intervals for multiple hypothesis testing.

To provide evidence in favor of the knowledge/demand effects hypothesis, we would expect to see those with less knowledge rating the QAnon-supporting candidate more negatively. However, we find the opposite. Those with *more* knowledge of QAnon and

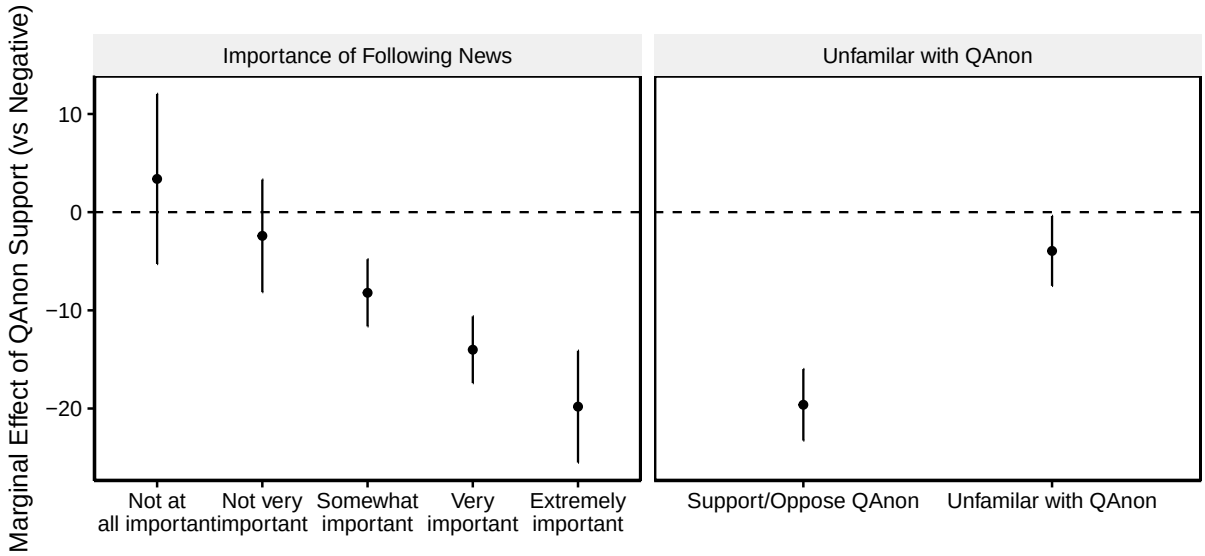

Figure B7: Marginal effects of QAnon-support (as compared to Negative) as moderated by expressed importance of following the news and knowledge of the QAnon conspiracy theory. Those with less knowledge are more approving of the QAnon-supporting candidate but do not express positive sentiments. Confidence intervals are at the 0.99 and 0.975 levels respectively.

who pay more attention to the news rate these candidates more negatively. In contrast to the knowledge-demand hypothesis, those with little knowledge of QAnon express more ambivalent attitudes toward the QAnon-supporting candidate. And further, those who say that it is "not at all important" or "not very important" to keep up with the news exact no statistical penalty on the QAnon-supporting candidate as compared to the negatively covered candidate. These results provide some support for the idea that these negative evaluations are real and associated with knowledge about the conspiracy theory and politics generally. In fact, lack of knowledge about QAnon leads to ambivalence from respondents.

Of course, we cannot conclusively rule out demand effects. However, the two different survey approaches, especially the conjoint experiment, and the additional statistical tests cut against the idea of demand effects, especially as a consequence of low knowledge, being responsible for the effects we observe.

B.6 Additional Pre-registered Tests and Notes

A few brief notes on our pre-registration plan:

- In our pre-registration plan for our vignette experiments, we said we would re-scale independent variables and some dependent variables to range between 0 and 1. To

facilitate interpretation given standard codings of these variables, and to allow for comparability across the vignette and conjoint experiment, we have deviated by leaving variables on their original scales. As transformations were linear, re-scaling would only change the interpretation of effect sizes, not the statistical significance of results.

- We said we would use bonferroni-corrected confidence intervals for particular tests. Upon reflection, these corrections were too liberal. We use more conservative corrections in the manuscript and appendix.

Below, we present additional pre-registered tests for completeness.

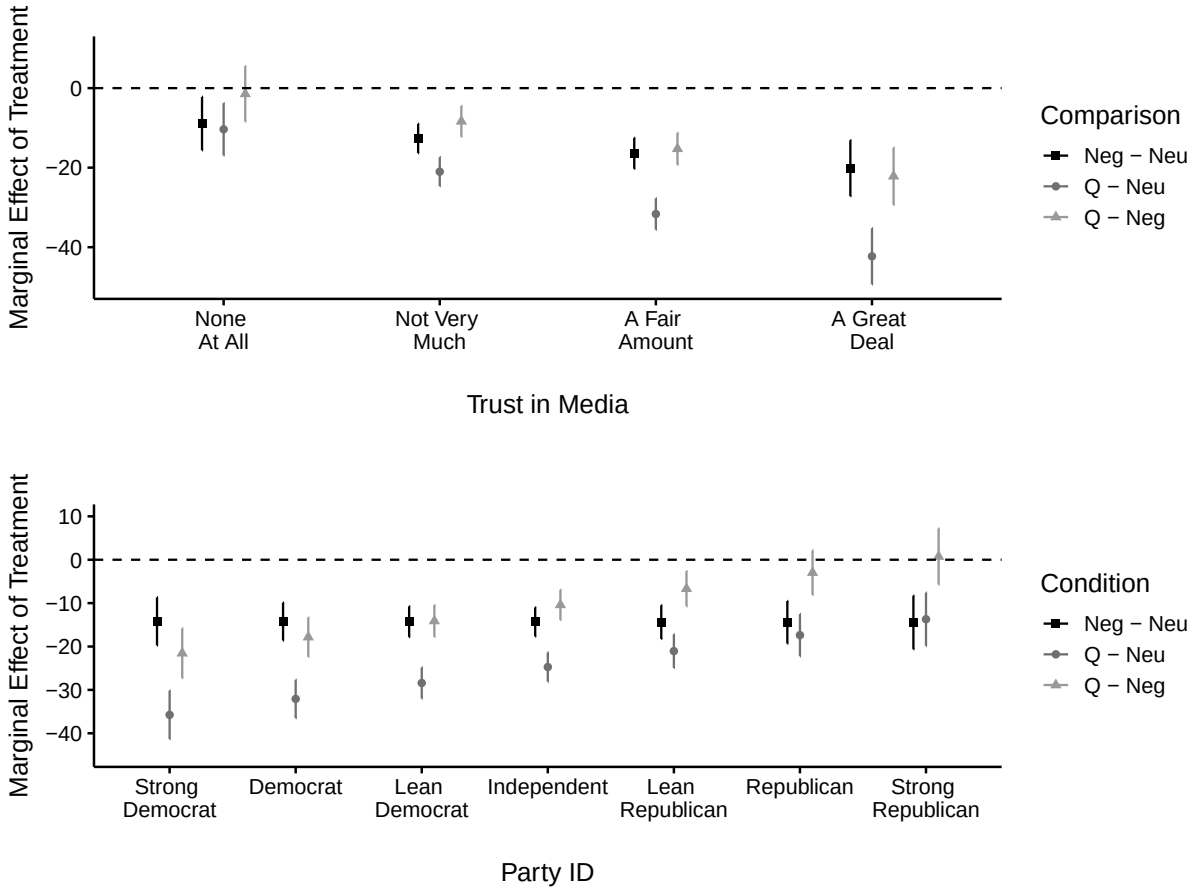

Figure B8: Marginal effects of treatment on candidate thermometer ratings for trust in media (party ID) without wave indicators. Confidence intervals are at the 0.996 (0.998) level. These effects are substantively similar to those using wave indicators.

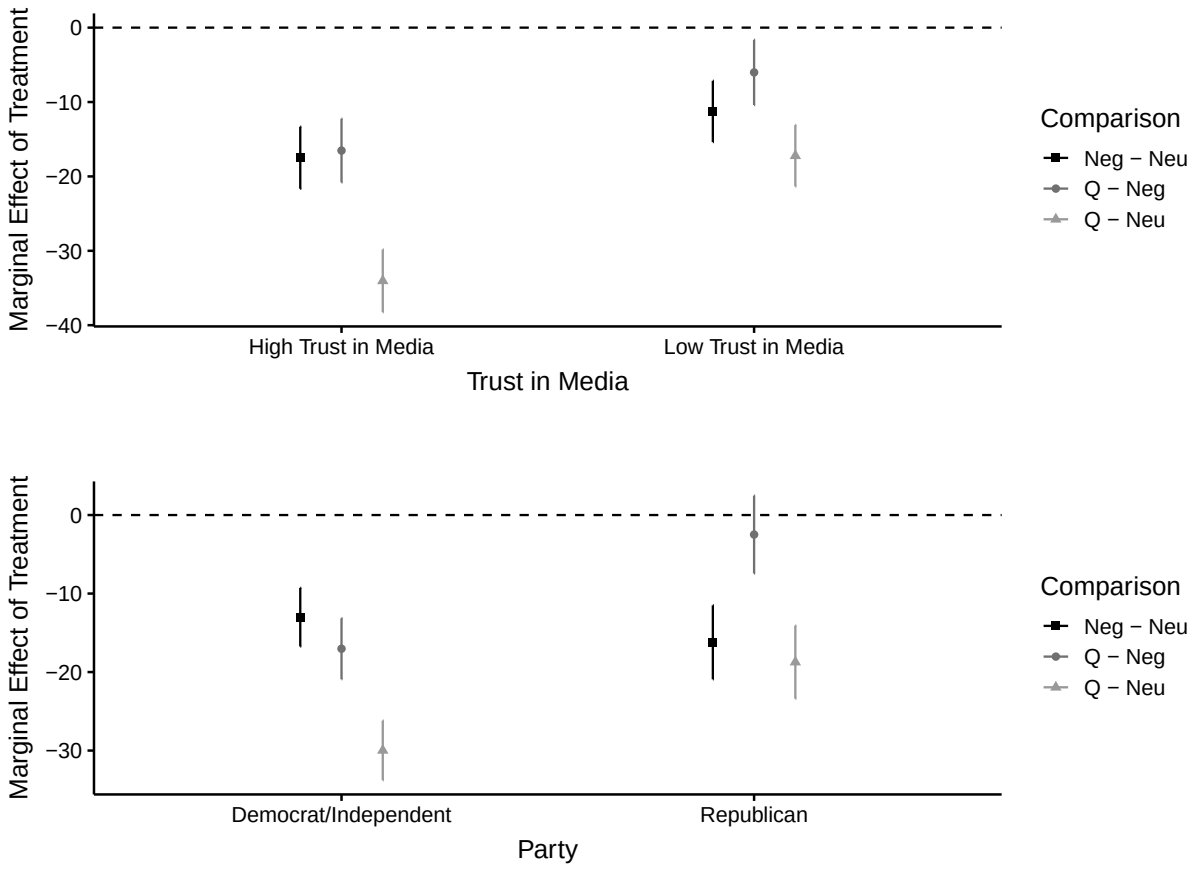

Figure B9: Marginal effects of treatment on candidate thermometer ratings for binary trust in media and binary party ID. Confidence intervals are at the 0.991 level. These effects are substantively similar to those using full scales.

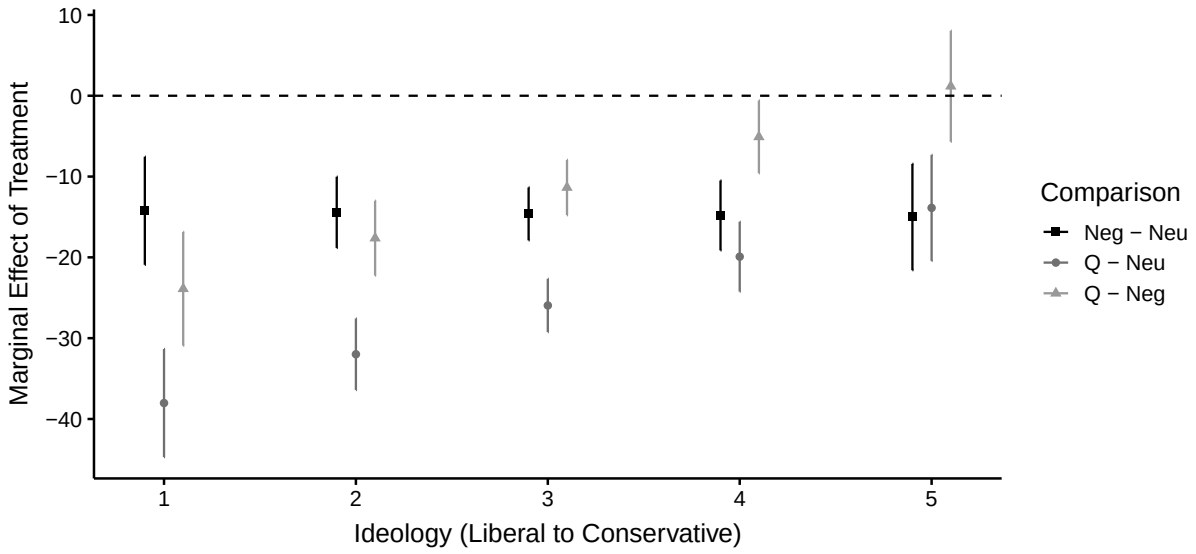

Figure B10: Marginal effects of treatment on candidate thermometer ratings for five-point ideology. Confidence intervals are at the 0.997 level. These effects are substantively similar to those using party ID.

C Conjoint Experiment

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

Some readers might be concerned that we framed candidates as either publicly supporting or not publicly supporting QAnon, but did not include an "actively oppose" option. We chose not to include this third possibility for several reasons.

One reason was methodological. Leeper, Hobolt and Tilley (2020) argue that comparisons between subgroup AMCEs (i.e., Democrats vs Republicans) are sensitive to the baseline category. Depending on our choice of the reference category, we may come to different conclusions about the consequences of QAnon support—however, this is not a concern for binary variables, as in our current design (Carey et al. 2022). Adding a third choice would complicate the interpretation of our results.

A second, and related, reason we made this choice is that we felt adding an "actively oppose" attribute would complicate the interpretation without adding much substantive insight. If respondents interpret "did not support" as tacit approval, and we still observe large penalties, we imagine that the AMCE between "support" and "actively oppose" would be even larger than what we observe here. We believe the more straightforward outcome would be, at minimum, no difference in AMCEs or, more likely, a strengthening of the effect.

Finally, we chose not to include an "actively oppose" attribute to better mirror what we believe was the reality in 2020 when we began our research. Unlike the stolen election conspiracy theory (which rose to prominence after we began our research) where Republicans, especially, have been asked to take a clear position (i.e., Trump won or lost), QAnon has not attracted the same clear-cut position-taking. For example, In December of 2020, the *Washington Post* published an article titled "Where Republicans in Congress stand on Trump's false claim of winning the election", tracking which Republicans supported, opposed, or made no comment with respect to Donald Trump's claims of election fraud. By contrast, articles from that time about QAnon support tend to focus on a few prominent candidates, implicitly or explicitly assuming support is rare.[12] Only when individuals play footsie with, or actively endorse, the conspiracy theory, are they labeled as supporters by the media. Otherwise, individuals were typically not asked about their beliefs and the default assumption is that silence is tantamount to opposition.

[12]For example, see this CNN article and this WaPo article.

Although these are simply our own rationalizations, the marginal means estimates in Figure C1 can provide some suggestive evidence to support our logic. What we see in this figure is that Republican and Democratic respondents in our survey are more likely to choose the candidate who did not support QAnon and less likely to choose the candidate who did support QAnon, on average. Given that, Democrats, in particular, select the non-supporter nearly two-thirds of the time, gives us some confidence that they are likely not viewing "did not support" as tacit approval. Indeed, this marginal mean is the largest among all attributes for Democrats. Democrats are more likely to vote for the non-supporter (0.64) than someone identifying as a Democrat (0.57). For Republicans, the marginal mean is smaller (0.56), but it is statistically equivalent in magnitude to a candidate who supports building a border wall (0.56) and low taxes (0.56). Taken together, these marginal means cut against the idea of a "tacit approval" interpretation.

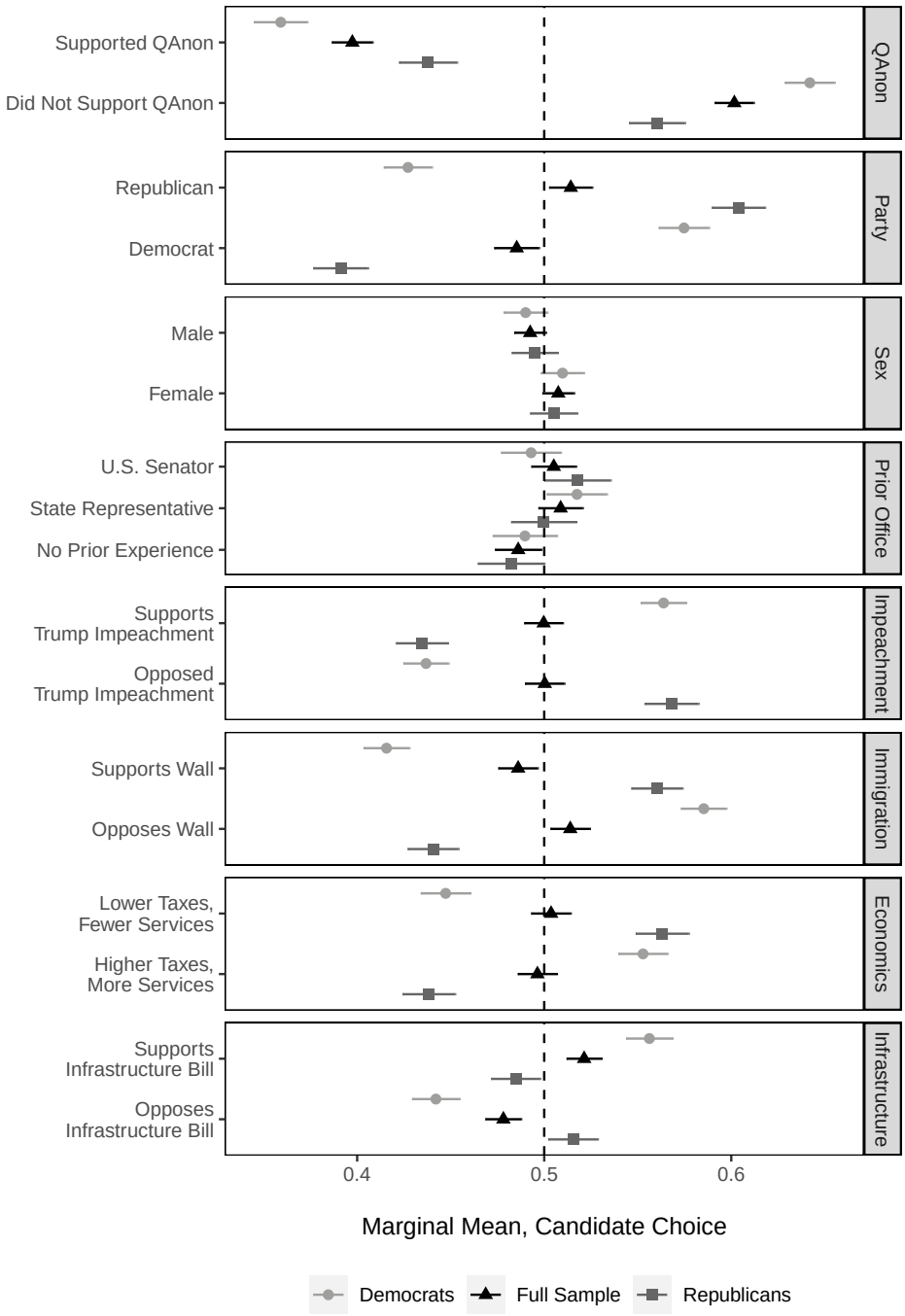

Figure C1: Marginal mean estimates of attributes on vote choice. QAnon support exerts a negative effect on Republican and Democratic vote choice.

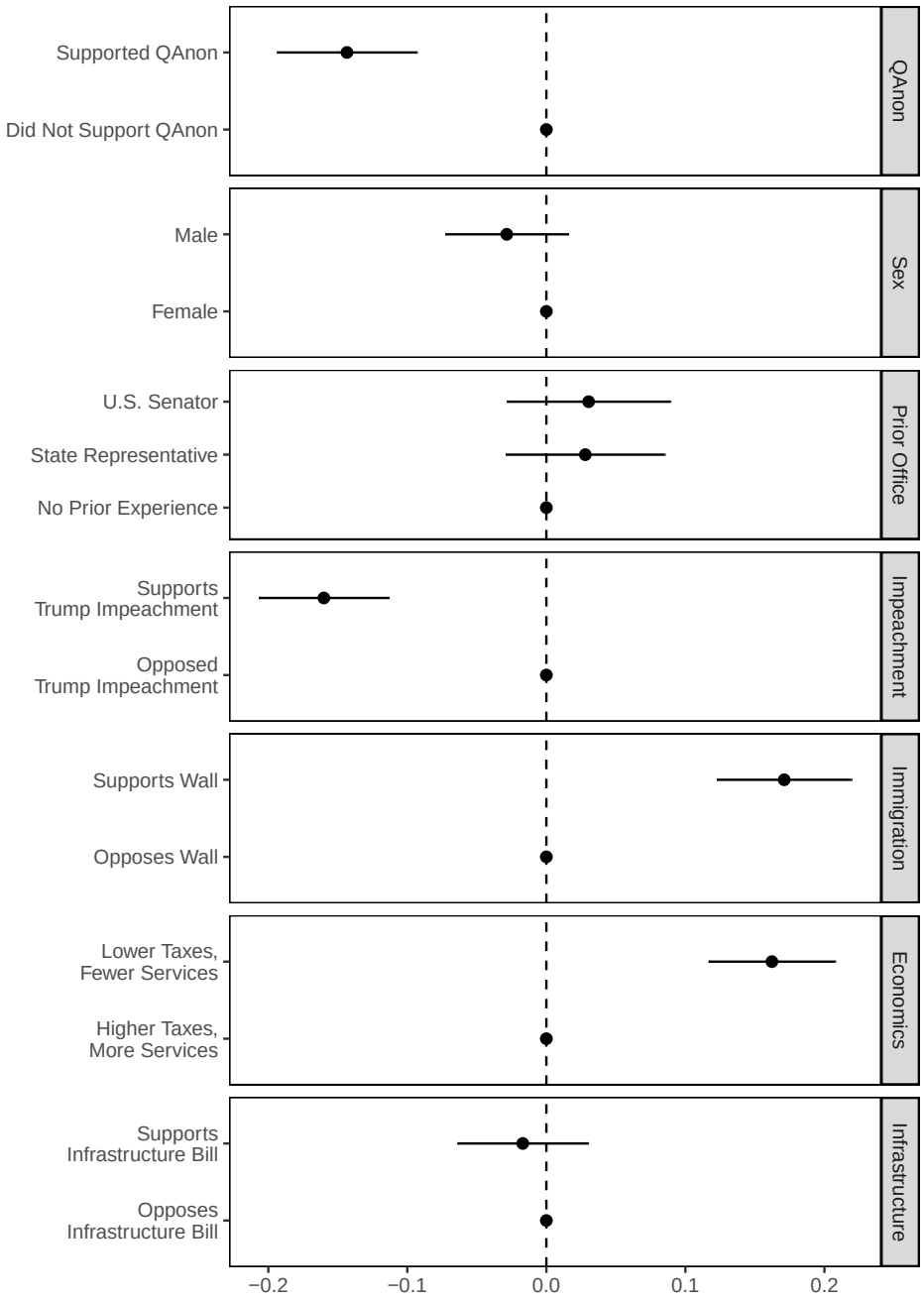

Figure C2: AMCE of each attribute on candidate choice in a Republican primary context. QAnon support causes a decline in vote choice. We include only choices between two Republican candidates and subset to Republican respondents to estimate this model. This test was not pre-registered.

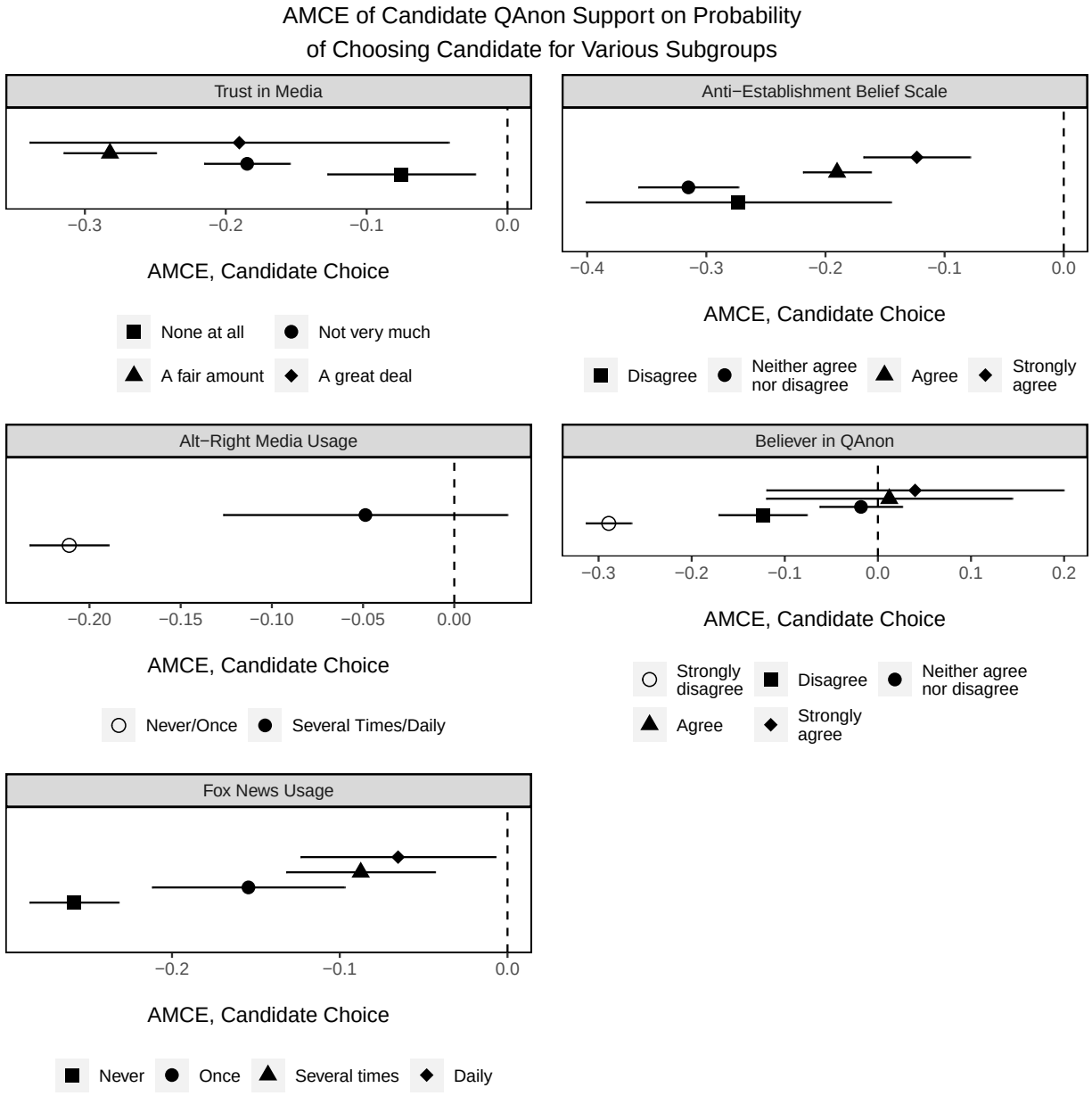

Figure C3: AMCE of QAnon support on candidate choice for each level of the moderator variable (as compared to no QAnon support). We round up values of the anti-establishment scale to the nearest whole value for tractability. Lower trust in media, anti-establishment beliefs, alt-right media usage (not pre-registered), and Fox news usage (not pre-registered) do not cause respondents to increase the probability of voting for a QAnon-supporting candidate. However, respondents who 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.

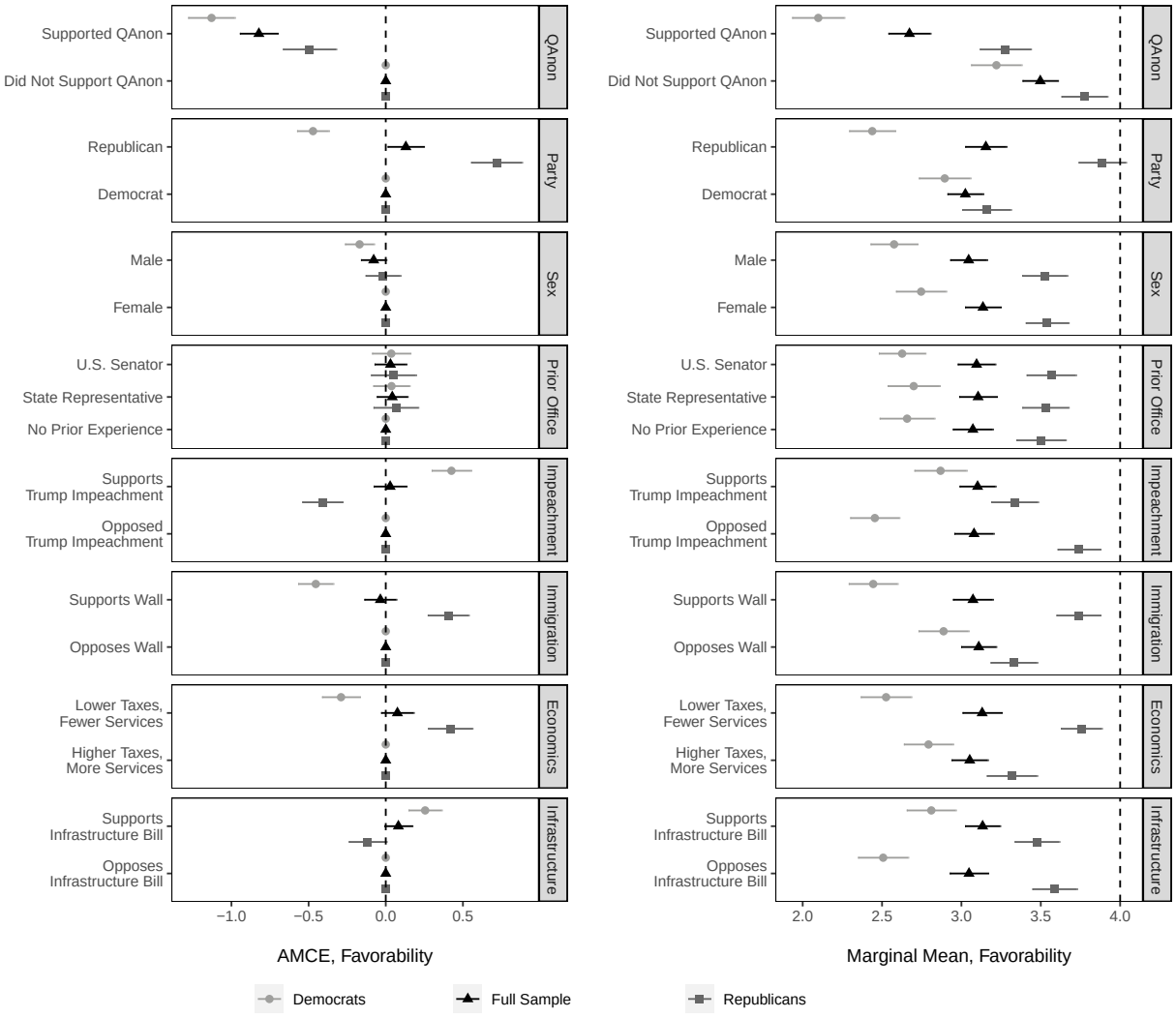

Figure C4: AMCE (left) and marginal means (right) of each attribute on 7-point favorability. QAnon support causes a decline in favorability, however, this effect is larger among Democrats than Republicans.

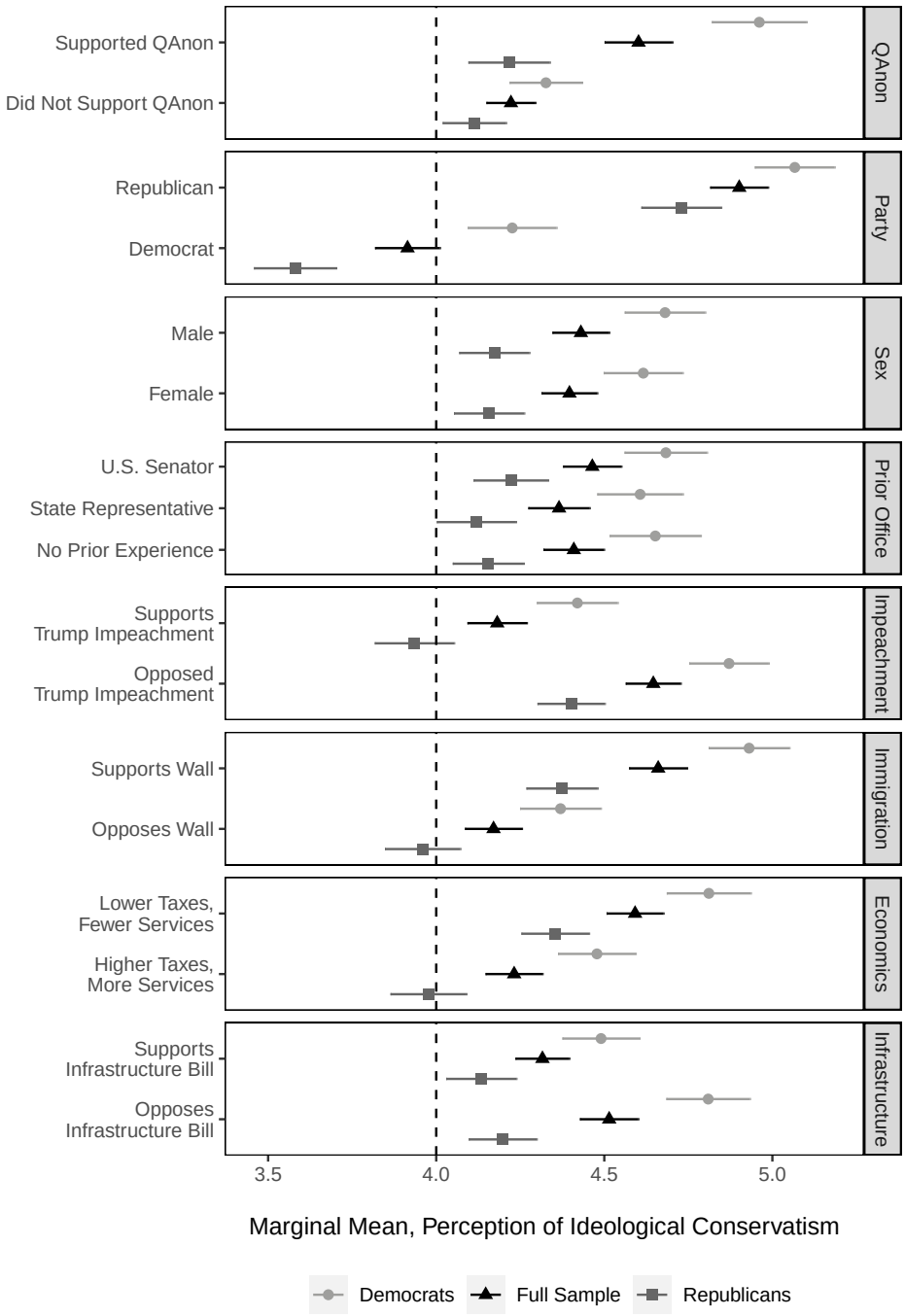

Figure C5: Marginal mean estimates of attributes on perceived ideology. QAnon support exerts a positive effect on Republican and Democratic perceptions.

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