Web Appendix

Web Appendix 1. Follower Data Collection via Wayback Machine

Given that we started collecting brand followership using the Twitter API only in February 2017, which does not include the period pre-election, we augmented our data via Wayback Machine (https://archive.org/web/) for the pre-election period. Specifically, we recover the number of followers for each brand in three time periods prior to the 2016 election: February 2016, May 2016, and October 2016. Wayback Machine collects snapshots of popular webpages over time. Using Wayback Machine we accessed the number of followers for all brands in our sample in February, May, and October 2016. As our initial data collection of Twitter users is always done between the 20th day and the last day of a month, we first search for observations in this time frame. If not available, we extend the observation to further dates until we cover the full month. We then connect this information with the Twitter follower data collection of February 2017. Twitter does not report a timestamp when a user joined a Twitter account, but the followers of accounts are sorted chronologically.[1] We approximate the users who joined the account between the pre-election date and February 2017 by looking at the difference in the number of users in the pre-election date from Wayback Machine and in February 2017 from our data, and leveraging the fact that Twitter sorts followers on the brand page by the date they joined the account. We acknowledge that this approach is only an approximation for the three pre-election periods (February, May, and October 2016).

[1] https://developer.twitter.com/en/docs/twitter-api/v1/accounts-and-users/follow-search-get-users/api-reference/get-followers-ids

Web Appendix 2. Bot Identification and Results

One concern with using Twitter data is that a non-negligible proportion of the accounts can be social bots.[2] Social bots are defined as algorithms that can automatically generate content and mimic human interactions (Ferrara et al. 2016). Since bots might systematically generate personas that are associated with conservatives or liberals, they may bias our results. To mitigate the problem of social bots, we removed accounts that were identified by Twitter as bot accounts in February 2018 after *The New York Times* brought to public attention the risk of bots on Twitter used to increase followership (Confessore et al. 2018). Additionally, we use the *Botometer* algorithm,[3] which detects the likelihood of an account being a bot based on features such as network, user, friends, temporal activity patterns, content, and sentiment. This algorithm has been shown to separate social bots from humans efficiently (Ferrara et al. 2016). We calculate the score for followers of the political accounts and remove those accounts with a score higher than 50% based on the algorithm (Shao et al. 2018). We identify and exclude 58,034 accounts as bot accounts. For the two focal political accounts, we find that they have a similar proportion of bots: the GOP (5%) and the DEM (3%). An analysis without removing the bots reveals similar results to those reported in the manuscript.

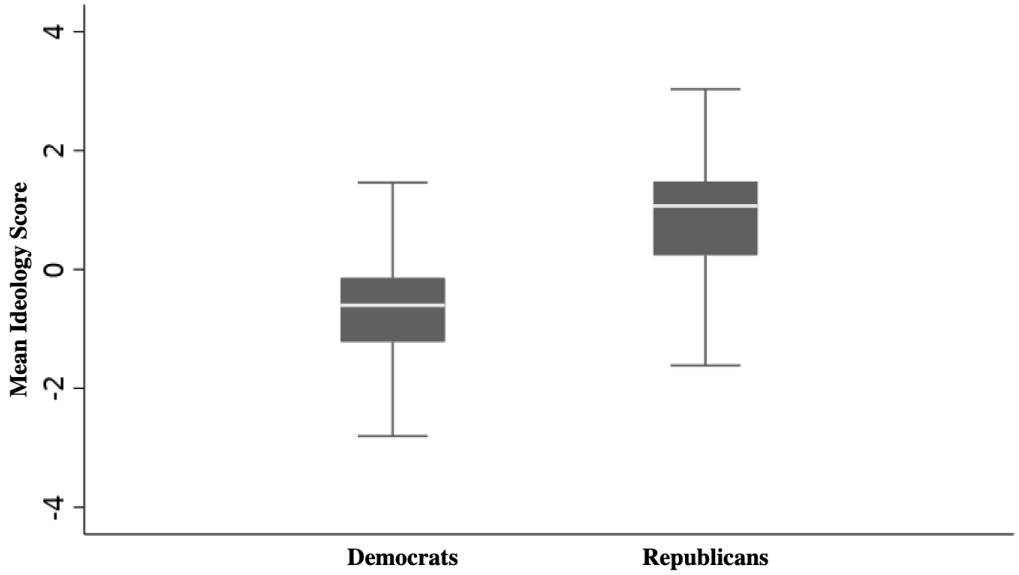
[2] https://www.nytimes.com/interactive/2018/01/27/technology/social-media-bots.html.
[3] https://github.com/IUNetSci/botometer-python

Web Appendix 3. Validation of Measures
Web Appendix 3a: Twitter Political Affiliation and the Ideology Scores of Barberà et al. (2015)

Barberà et al. (2015) build on the logic of latent space and spatial Twitter following models to assess the political affiliation of Twitter users. The authors implement a mathematical approximation using correspondence analysis to ensure the method is computationally tractable given the large-scale Twitter network. Thus, we validate our measure of political affiliation by comparing the Twitter political account followership with the ideology scores of the same Twitter users calculated by Barberà et al. (2015). For 21,305 users in our sample (13,703 Democrats and 7,602 Republicans) we also have a corresponding ideology score calculated by Barberà et al. (2015).

Figure A1 shows boxplots of the ideology scores of the Twitter users from the sample of users of Barberà et al. (2015) that were also part of our dataset, split by the political account these users followed (GOP or DEM). An ideology score below 0 indicates a Democratic political affiliation, while a score above 0 indicates a Republican political affiliation according to Barberá et al. (2015). We find a high correlation between our political affiliation metrics and Barberá et al.'s ideology score (r = 0.64, $p < 0.001$, n = 21,305). The results confirm that the followership of the political party account serves as a reasonable proxy of political ideology.

Figure A1. Twitter Political Affiliation and the Ideology Scores of Barberà et al. (2015)

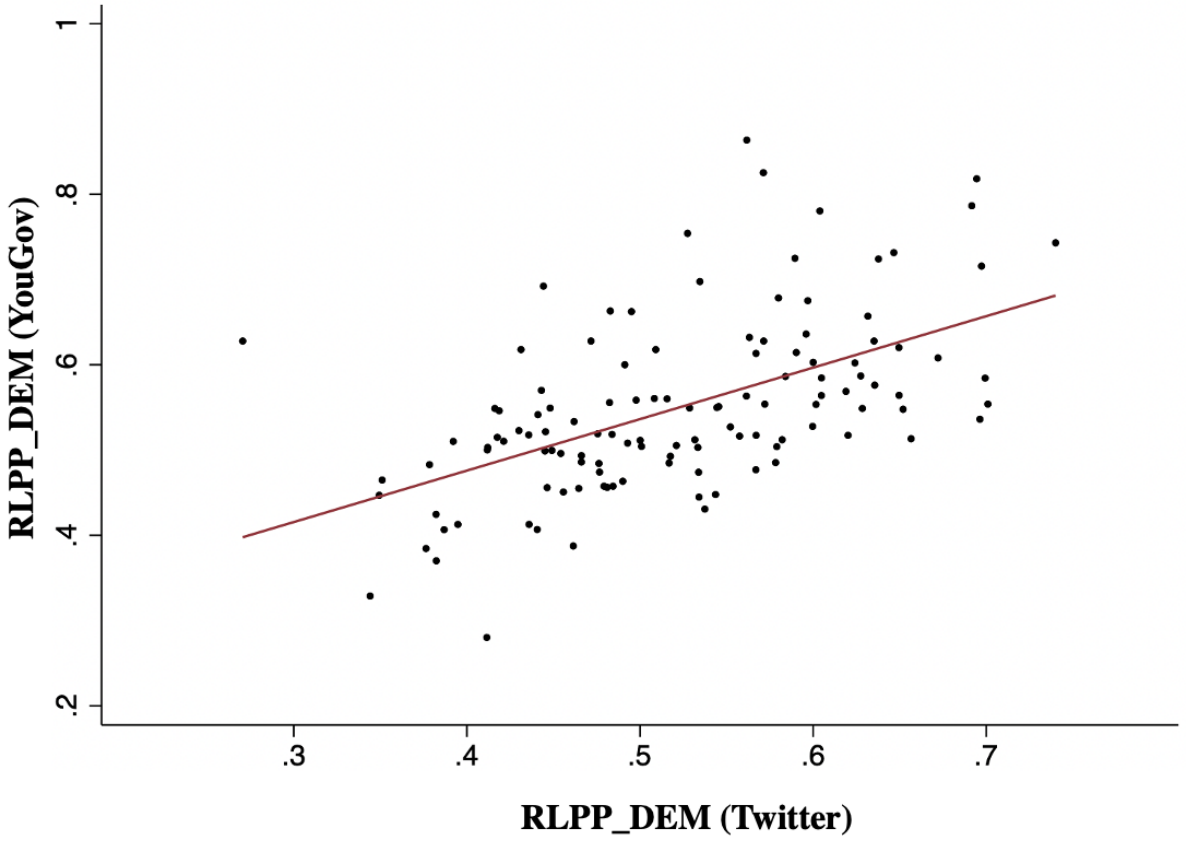


Note: Mean Ideology Score – Ideology score for users identified as Democrats or Republicans in our sample using the calculated ideology score of Barberà et al. (2015): point estimates and 95% confidence intervals.

Web Appendix 3b. Political Affiliation Based on Twitter and the YouGov Dataset

For a subset of 120 brands from the Twitter dataset we have data for stated brand ownership and the stated political affiliation for a random sample of U.S. respondents to the YouGov survey. We find a high correlation between the Twitter and the YouGov RLPP_DEMs (r = 0.55, $p < 0.001$, n = 120). Figure A2 shows the relationship between RLPP_DEM of ownership according to the YouGov survey and our measure of Relative Lift Preference Partisanship.

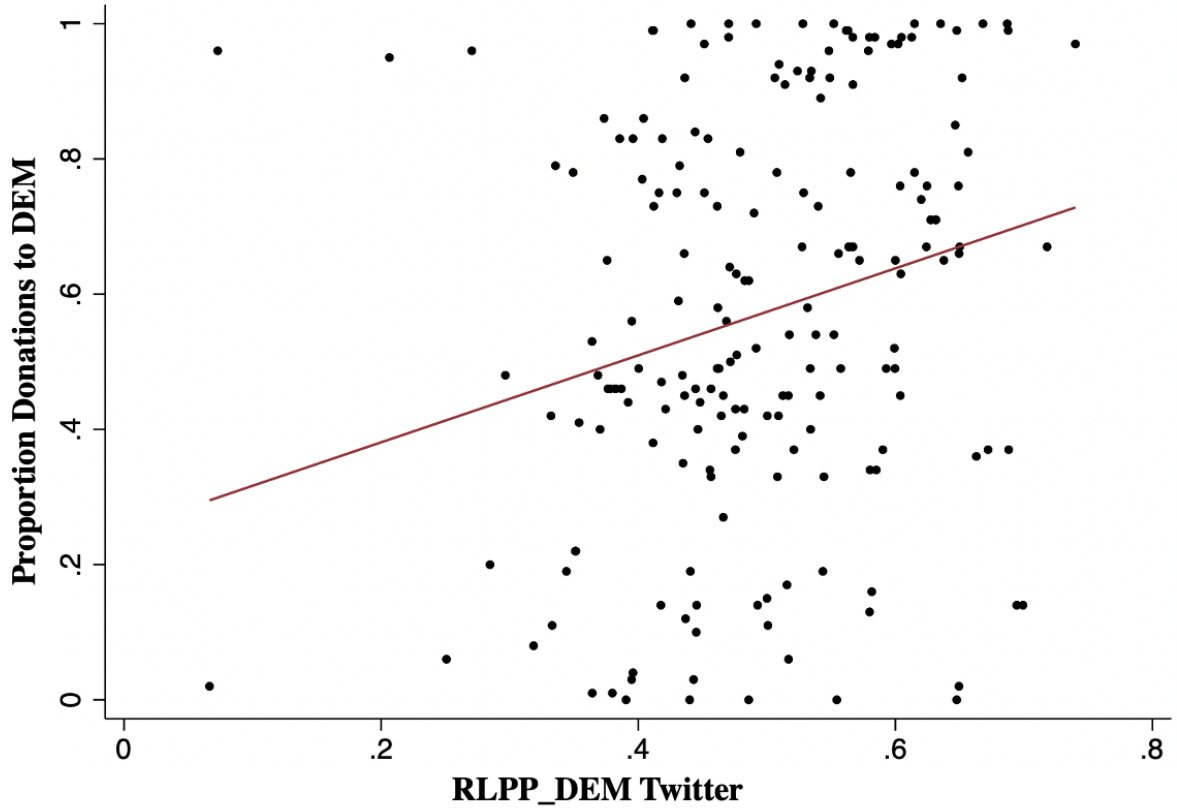
Figure A2. The Relationship between Brand Political Affiliation based on Twitter and YouGov



Web Appendix 3c. Political Affiliation Based on Twitter and Donations goodsuniteus.com

We relate our measure of brand political affiliation to political donations made by these brands. For a subset of 192 brands, we obtain from goodsuniteus.com information about political donations made by the brand and its senior employees. We find a positive correlation between our RLPP measure and the proportion of donations to the political party ($r = 0.24$, $p < 0.001$, $n = 192$). Thus, the preference partisanship of a brand seems to be affected by, or at the minimum correlated with, the brand's political donation distribution.

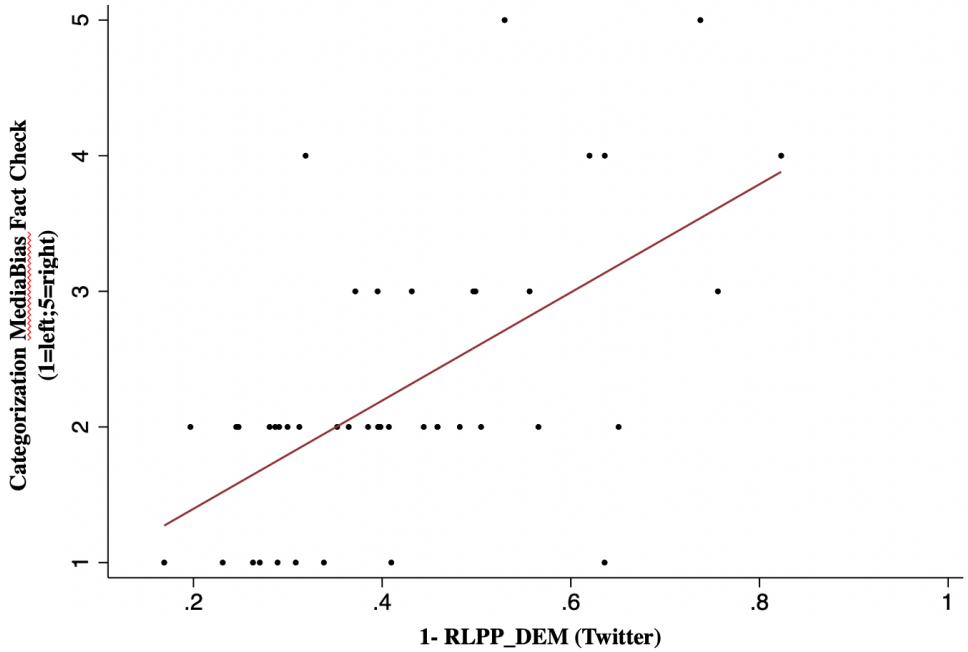
Figure A3. The Relationship between Brand Political Affiliation based on Donations Twitter and goodsuniteus.com



Web Appendix 3d. Media Bias Measures Based on Mediabiasfactcheck.com and Media Preference Partisanship Based on Twitter

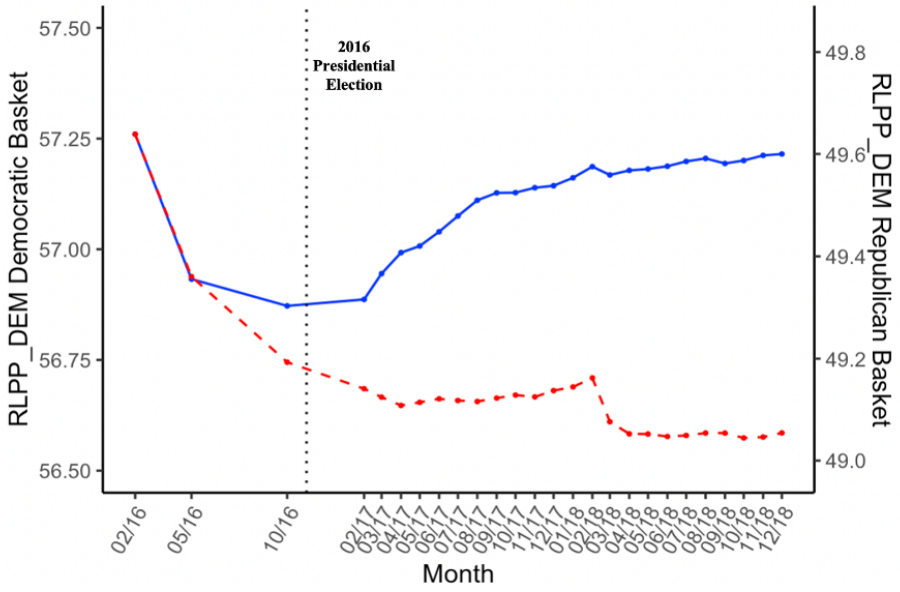
The independent organization mediabiasfactcheck.com reports the ideological placement and media bias on a five-point scale from left bias to right bias of different media outlets. For 43 media sources we have an overlap between our political RLPP_DEM measure and mediabiasfactcheck scores. Figure A4 displays the relationship between the score of the media outlet with respect to its media bias rated by the platform media bias/fact check (1 = left bias; 5 = right bias; y-axis, https://mediabiasfactcheck.com/) and our measures of Relative Lift Preference Partisanship (x-axis). The result indicates a substantial positive Spearman correlation coefficient (Relative Lift Preference Partisanship: 0.57, $p < 0.001$) between our preference partisanship measures and the ideological placement of media outlets by an independent organization, mediabiasfactcheck.com. This provides further validity for our measure of preference partisanship.

Figure A4. The Relationship between Media Political Affiliation based on Twitter and Mediabiasfactcheck.com



Web Appendix 4. The Evolution of the Democratic Political Affiliation (RLPP_DEM_Basket) of the User Brand Basket Over Time for DEM and GOP Twitter Followers – Median

Figure A5. Median RLPP_DEM_Basket Evolution



Note: The blue (solid) line shows the evolution of the median Democratic basket of Democrats on Twitter, and the red (dashed) line shows the evolution of the median Democratic basket of Republicans on Twitter.The vertical dashed line marks the 2016 presidential election.

Web Appendix 5. Alternative Measure RLPP

Our measure of polarization focuses on the share of political support among the brand followers/buyers for one side of the political spectrum. To rule out that polarization is also determined by the overall degree of (or lack of) political support of the brand followers, we recalculate our measure of RLPP incorporating the middle-ground followers (followers following both political parties or none) by calculating the RLPP as follows:

$$RLPP_{bp} = \frac{LPP_{bp}}{LPP_{bp(GOP)} + LPP_{bp(DEM)} + LPP_{bp(No\ Political\ Party\ or\ Both\ Political\ Parties)}}$$

We then re-run the analysis in Table 1 in the main manuscript, this time using the alternative measure of RLPP that also includes brand followers that follow no political account or both. The results again show an increase of polarization after the election.

Table A1: Political Affiliation User Basket Pre- and Post-Election (Alternative Measure RLPP)

RLPP DEM (in %)	**Coef. (Std. Err.)**
Post-Election Dummy	0.106 (0.010)***
Month	-0.006 (0.001)***
Post-Election Dummy x DEM	0.086 (0.013)***
Month x DEM	0.022 (0.001)***
Constant	45.700 (0.008)***
N	4,586,036
N_{users}	176,386
$R^2_{overall}$	0.246

Note: User fixed effects included. Standard errors clustered at the user level. The political affiliation of a user is captured by the user fixed effect. ***$p < 0.01$

Web Appendix 6. Basket Evolution of Democratic, GOP, and Trump Followers

To further understand commonalities and differences of Donald Trump followers versus GOP followers, we separately investigate the polarization comparing Democratic followers to GOP-only followers, Trump-only followers, and followers of both GOP and Trump. The graphs of the basket evolution as well as the regression results demonstrate that the polarization persists across all groups, but GOP supporters show a stronger polarization compared to supporters of Donald Trump.

Figure A6. The Evolution of the Political Affiliation (RLPP_DEM_Basket) of the User Brand Basket Over Time for DEM, GOP, and Trump Twitter Followers

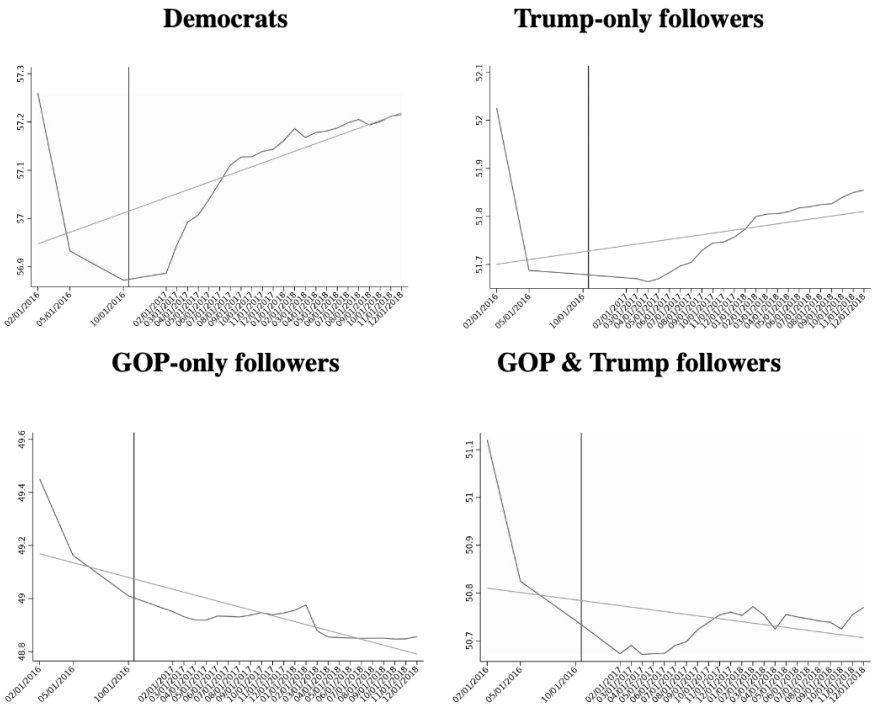


Table A2: Political Affiliation of User Basket Pre- and Post-Election (Democrats, GOP, and Trump Followers)

	Democrats vs. Republicans	Democrats vs. Republicans not following Trump	Democrats vs. Republicans following Trump	Democrats vs. Trump Only
RLPP_DEM (in %)	**Coef. (Std. Err.)**	**Coef. (Std. Err.)**	**Coef. (Std. Err.)**	**Coef. (Std. Err.)**
Post-Election Dummy	-0.164 (0.011)***	-0.159 (0.012)***	-0.209 (0.032)***	-0.266 (0.003)***
Month	-0.011(0.001)***	-0.012 (0.001)***	-0.004 (0.002)**	0.006 (0.000)***
Post-Election Dummy X DEM	0.036 (0.013)***	0.031 (0.014)**	0.081 (0.032)**	0.138 (0.008)***
Month X DEM	0.019 (0.001)***	0.020 (0.001)***	0.012 (0.002)***	0.002 (0.000)***
Constant	53.155 (0.008)***	53.305 (0.008)***	56.550 (0.009)***	52.272 (0.003)***
N	4,586,036	4,371,068	2,697,292	26,989,040
N_{users}	176,386	168,118	103,742	1,038,040
$R^2_{overall}$	0.2942	0.3035	0.0860	0.0315

Note: User fixed effects included. Standard errors clustered at the user level. The political affiliation of a user is captured by the user fixed effect. $^{**}p < 0.05$, $^{***}p < 0.01$

Web Appendix 7. #Democratic and #Republican Brands in Basket

We repeated the regression in Table 1 with the dependent variable being the number of Democratic or Republican brands that a user follows in each month. The results show a significant positive interaction between the post-election dummy and the political affiliation for Democratic ($\beta = 0.382(0.015)***$) and a negative interaction for Republican brands ($\beta = -0.158(0.011)***$). This further demonstrates the increase in polarization by Democrats adding more Democratic brands to their basket compared to Republicans, while adding fewer Republican brands to their basket compared to Republicans.

Table A3: Evolution of #Democratic Brands in Basket

Number Democratic Brands	**Coef. (Std. Err.)**
Post-Election Dummy	0.872 (0.010)***
Month	0.059 (0.001)***
Post-Election Dummy x DEM	0.382 (0.015)***
Month x DEM	0.049 (0.001)***
Constant	8.123 (0.009)***
N	4,586,036
N_{users}	176,386
$R^2_{overall}$	0.024

Note: User fixed effects included. Standard errors are clustered at the user level. The political affiliation of a user is captured by the user fixed effect. Month is a variable that captures the linear year-month time trend. ***$p <$ 0.01

Table A4: Evolution of #Republican Brands in Basket

Number Republican Brands	**Coef. (Std. Err.)**
Post-Election Dummy	0.751 (0.009)***
Month	0.055 (0.001)***
Post-Election Dummy x DEM	-0.158 (0.011)***
Month x DEM	-0.011 (0.001)***
Constant	5.315 (0.006)***
N	4,586,036
N_{users}	176,386
$R^2_{overall}$	0.021

Note: User fixed effects included. Standard errors are clustered at the user level. The political affiliation of a user is captured by the user fixed effect. Month is a variable that captures the linear year-month time trend. ***$p <$ 0.01

Web Appendix 8. YouGov Variable Measurement

Below we detail the YouGov survey questions, using the airline product category as an example.

1) **Consideration**
   "When you are in the market next to book a flight, from which of the following would you consider purchasing a ticket?" (respondent was presented with a list of up to 40 brands)

2) **Likelihood to Buy**
   "From which of these would you be most likely to purchase?" (respondent was presented with a list of considered brands in the category; 1 = chosen brand)

3) **Brand Ownership**
   "Have you purchased a flight from any of the following airlines in the past 12 months?" (respondent was presented with a list of brands in the category; 1 = yes, 0 = no)

4) **WOM**
   "Which of the following airlines have you talked about with friends and family in the PAST TWO WEEKS (whether in-person, online, or through social media)?" (respondent was presented with a list of brands in the category; 1 = yes, 0 = no)

Web Appendix 9. Validation of Brand Political Affiliation, Nielsen

To test the validity of our geography-based Nielsen proxy for political affiliation, we compare the correlations between the political affiliation from our Nielsen measure and the Twitter measure of brand political affiliation for a subset of brands that overlap between the two datasets. First, we find a substantial and significant correlation between the two measures (n brands Nielsen = 281, $\rho = 0.3515, p < 0.001$). Additionally, we rerun the analysis in Table 3 in the main manuscript using the Nielsen retail data for the subset of brands for which we also have access to the Twitter brand political affiliation. For this subset, we compare the results using the Nielsen and the Twitter proxy of political brand affiliation. Table A5 demonstrates that the results hold for this subset of brands when using either the Nielsen or the Twitter proxy for political brand affiliation. This provides a robustness test for our findings both in terms of the sample of brands and the proxy for political affiliation.

Table A5: Comparing Brand Political Affiliation Measures Based on Twitter and Nielsen

	Nielsen - Share_DEM$_{sm}$	*Twitter - Share_DEM$_{sm}$*
	Coef.	**Coef.**
Post-Election Dummy	0.0214 (0.0032)***	0.1007 (0.0082)***
Month	0.0015 (0.0002)***	0.0040 (0.0005)***
Post-Election Dummy X *DEM_voting_results*	0.1014 (0.0060)***	0.1759 (0.0151)***
Month X *DEM_voting_result*	-0.0069 (0.0004)***	-0.020 (0.0010)***
Price Control	-0.0038 (0.0016)**	-0.0011 (0.0040)
Constant	51.68 (0.0009)***	58.87 (0.0028)***
N	934,452	934,452
N_{stores}	25,957	25,957
$R^2_{overall}$	0.0501	0.0127

Note: Store fixed effects included. The political affiliation of a store is captured by the store fixed effect. Month is a variable that captures the linear year-month time trend. Standard errors clustered at the store level. **$p < 0.05$, ***$p < 0.01$

Web Appendix 10. Analyzing a Specific Product Category – Soft Drinks

To better understand the drivers of the observed increase in demand for Democratic brands in Democratic counties, we look at household-level purchase behavior using the Nielsen Homescan Consumer Panel, in which we observe purchases at the individual household level. Specifically, we investigate two different mechanisms that are potentially driving the increase in demand: increase in product choice of Democratic brands and increase in quantity purchased of Democratic brands. In order to disentangle the two possible sources of the observed effect, we focus on one product category ("Soft Drinks"). We choose this category because it has the widest range of political brand affiliations across brands in the category. In total, we observe 265 soft-drink brands across all counties. We restrict our analysis to brands that were bought at least once in every month of our data period within a county. The most Democratic soft-drink brand we observe is "Rock Creek" with a BPA_DEM of 91%, and the least Democratic brand is "Dr. Enuf" with a BPA_DEM of 22%.

In order to disentangle the effect of brand choice and quantity, we conduct three separate analyses:

1) BPA_DEM_S.Drink_Basket – We first replicate the analysis in Table 3 in the main manuscript but this time at the household level, for the specific category, based on the voting behavior in the household's county. Specifically, we calculate the BPA_DEM_S.Drink_Basket similar to Equation 5 in the main manuscript as follows:
   $BPA\_DEM\_S.Drink\_Basket_{it} = \frac{\sum_{b=1}^{N_i} Q_{itb} \times BPA\_DEM_b}{\sum_{b=1}^{N_i} Q_{itb}}$,
   where N_i is the set of brands available in household *i*'s county, and Q_{itb} is the quantity household *i* purchased of brand *b* in shopping trip *t*.

2) Brand choice – To assess the brand choice, we look at the political affiliation of the unique brands purchased by household *i,* not taking into account the quantity purchased. Specifically,
   $Unique\ Brands\_DEM\_S.Drink_{it} = \frac{\sum_{b=1}^{N_i} I(Q_{itb}>0) \times BPA\_DEM_b}{\sum_{b=1}^{N_i} I(Q_{itb}>0)}$
3) Quantity – To investigate if consumers simply increased their quantity of soft-drink purchases per brand we calculate:
   $Quantity_{it} = \frac{\sum_{b=1}^{N_i} (Q_{itb})}{\sum_{b=1}^{N_i} I(Q_{itb}>0)}$

We run a regression of each of the three dependent variables above on a shopping trip linear time trend, post-election dummy, average price of soft drinks in the focal shopping trip, the interaction between the shopping trip time trend or post-election dummy and Democratic voting behavior in the household's county (DEM_voting_result), and household fixed effects, which capture the household's stable political affiliation and other time-invariant effects.

The first column in Table A6 shows that the effect reported at the store level replicates to the household level and the soft-drink category. Specifically, soft-drink baskets of households in Democratic counties became more Democratic after the 2016 election. Looking at the source of users' baskets becoming more Democratic in Democratic counties, we find that the effect is driven by unique brands purchased (column 2 in Table A6) and not an increase in the quantity of products

purchased given a brand purchase (column 3 in Table A6). This analysis suggests that, at least for soft drinks, after the 2016 election Democrats added brands to their basket that are more Democratic rather than purchased a higher quantity of brands in their basket.

To further investigate the robustness of the effects within the category of soft drinks we investigate two subsets of the whole soft-drink category: in the first subset we repeat our analyses looking only at the 30 top selling brands and in the second subset we only look at the 15 most extreme Democratic and 15 most extreme Republicans brands based on their political affiliation in 2015 and again repeat the analysis in Table A6. Both analyses show polarization in soft drink purchases by consumers living in Democratic counties. Figure A7 shows the evolution of the users' baskets for the 30 most selling soft drinks in terms of sales over time and demonstrates a visible acceleration in polarization for the Democratic basket of soft drinks.

Figure A7. Evolution of User Basket of 30 most selling Soft-Drink Brands

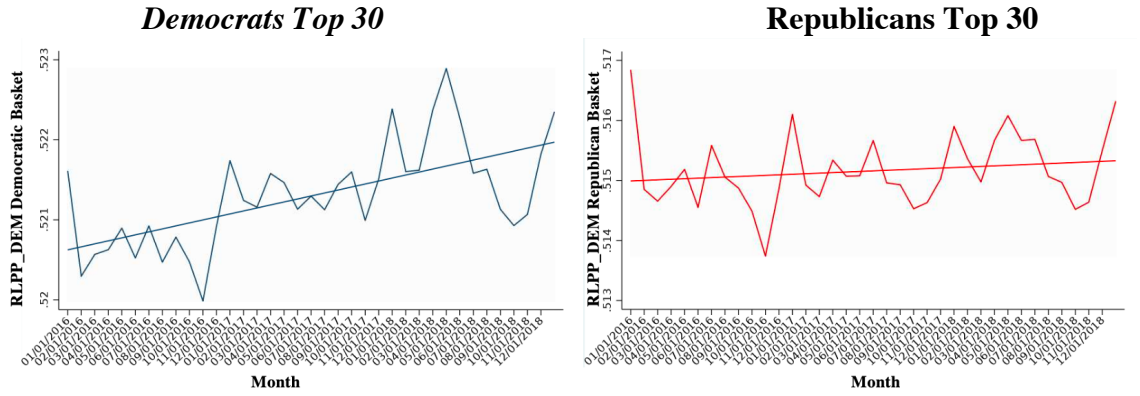


Table A6: Nielsen Homescan Consumer Panel

	BPA DEM S.Drink Basket	Unique Brands S.Drink_DEM	Quantity S.Drink
Post-Election Dummy	0.026 (0.021)	0.027 (0.021)	0.0013 (0.0227)
Trip Time Trend	-0.000 (0.000)	-0.000 (0.000)	0.0015 (0.0003)***
Post-Election Dummy X DEM_voting_results	0.091 (0.037)**	0.090 (0.037)**	-0.0050 (0.0405)
Trip Time Trend X DEM_voting_results	-0.000 (0.001)	-0.000 (0.001)	-0.0013 (0.0006)**
Price Control	-0.047 (0.001)***	-0.047*** (0.001)***	-0.1718 (0.0012)***
Constant	52.087 (0.005)***	52.081*** (0.005)***	2.8792 (0.0052)***
N_{HH}	32,728	32,728	32,728
N	953,672	953,672	953,672
$R^2_{overall}$	0.01	0.01	0.026

Note: Household (HH) fixed effects included. The political affiliation of a HH is captured by the HH fixed effect. $^{**}p < 0.05$, $^{***}p < 0.01$

Web Appendix 11. Brands Involved in Political Actions after the 2016 Presidential Election

We mined Donald Trump's Twitter account and several popular press sources to create an extensive list of brand political events or actions (n = 353) taken by 101 unique brands. We then classify the events into four different groups: events in which brands took an active action against Donald Trump (n = 145), were attacked by Donald Trump on his Twitter feed (n = 154), supported Donald Trump (n = 24), or were praised by Donald Trump (n = 30). Note that brands can take multiple actions and can even take actions in multiple categories. Thirty-nine of the brands had events in more than one category.[4]

We expect actions opposing Donald Trump or brands being attacked by Donald Trump to lead the brand to become more Democratic, while we expect the opposite for brands that supported or were praised by Donald Trump. In order to investigate this effect, we regress the RLPP_DEM of the brand in any particular month between February 2016 and December 2018 on a dummy variable equal to 0 if the brand has not taken an action in that category up to the focal month, and 1 for any month after an action has been taken by the brand.[5] As can be seen in Table A7, we find that only brands that took an action against Donald Trump became significantly more Democratic.

Table A7: Polarization of Brands Taking a Stand

RLPP_DEM (in %)	**Coef.**
Action against Trump	1.103 (0.102)***
Attacked by Trump	0.150 (0.118)
Supporting Trump	-0.287 (0.182)
Praised by Trump	0.086 (0.176)
Month	0.062 (0.006)***
Constant	50.538 (0.057)***
N_{brands}	101
N	2,626
$R^2_{overall}$	0.027

Note: User fixed effects included. The political affiliation of a user is captured by the user fixed effect. ***p < 0.01

For a list of all the events and their classification, please see the csv file in the Supplemental Materials.

[4] Excluding brands whose events can be attributed to multiple categories or assigning brands to the category with the most common events leads to similar results.

[5] We find similar results when operationalizing the event dummy for 3 or 6 months after the event.

References

Barberà P, Jost JT, Nagler J, Tucker JA, Bonneau R (2015) Tweeting from left to right: Is online political communication more than an echo chamber? *Psychol. Sci.* 26(10):1531–1542.

Confessore N, Dance GJ, Harris R, Hansen M (2018) The follower factory. The New York Times 27, https://www.nytimes.com/interactive/2018/01/27/technology/social-media-bots.html.

Ferrara E, Varol O, Davis C, Menczer F, Flammini A (2016) The rise of social bots. *Communications ACM*. 59(7):96–104.

Shao C, Ciampaglia GL, Varol O, Yang KC, Flammini A, Menczer F (2018) The spread of low-credibility content by social bots. *Nature Communications* 9(1):4787.