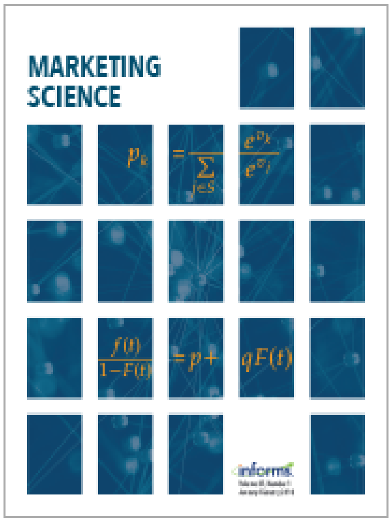

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Frontiers: Polarized America: From Political Polarization to Preference Polarization

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Abstract. In light of the widely discussed political divide and increasing societal polarization, we investigate in this paper whether the polarization of political ideology extends to consumers' preferences, intentions, and purchases. Using three different data sets—the publicly available social media data of over three million brand followerships of Twitter users, a YouGov brand-preference survey data set, and Nielsen scanner panel data—we assess the evolution of *brand-preference polarization*. We find that the apparent polarization in political ideologies after the election of Donald Trump in 2016 stretches further to the daily lives of consumers. We observe increased polarization in preferences, behavioral intentions, and actual purchase decisions for consumer brands. Consistent with compensatory consumption theory, we find that the increase in polarization following the election of Donald Trump was stronger for liberals relative to conservatives, and that this asymmetric polarization is driven by consumers' demand for "Democratic brands" rather than the supply of such brands. From a brand perspective, there is evidence that brands that took a political stance observed a shift in their customer base in terms of their customers' political affiliation. We provide publicly available (http://www.social-listening.org) access to the unique Twitter-based brand political affiliation scores.

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Keywords: political marketing • social media • data mining • political polarization • branding

1. Introduction

The political divide in the United States is well documented and is said to have widened in recent years.[1] Additionally, there is some evidence that the growing political polarization since the victory of Donald Trump in the 2016 U.S. presidential election[2] has been even stronger for liberals compared with conservatives.[3] In the current political climate, stereotypes abound: Republicans think of Democrats as godless, Nordstrom-loving weenies who read the *Atlantic* while sipping their lattes, whereas Democrats dismiss Republicans as ignorant religious fanatics who are obsessed with the National Rifle Association, drink Budweiser, watch Fox News, and surf the Drudge Report.[4]

In line with this claim, the far-reaching impact of political orientation has been shown to extend to many different aspects of life, such as a person's social identity (Ordabayeva 2019) and personality (Sibley et al. 2012). Several studies report that conservatives and liberals[5] exhibit different patterns in day-to-day behaviors such as grocery shopping, movie choices, recycling, charity choices, complaints/disputes, and lifestyle choices (Winterich et al. 2012, Khan et al. 2013, Kidwell et al. 2013, Roos and Shachar 2014, DellaPosta et al. 2015, Jung et al. 2017). In this paper we ask the following questions: (1) Can we use publicly available social media data to assess the political divide in brand preferences? And (2) how did the political divide in brand preferences evolve over time and particularly since the 2016 election?

Social media in general and Twitter in particular play an influential role in presidential elections and became controversial communication channels during the campaign and administration of President Trump.[6] Independent of Twitter's effect in possibly shaping political opinions, we explore Twitter's role as a window into people's preferences, beliefs, and values to create a picture of one's persona (Culotta and Cutler 2016) and relate it to political polarization. On social media platforms such as Twitter, individuals "announce" via the accounts they follow their preferences and values. The Twitter accounts that users follow reflect the users' political affiliation, the stores they like, the sports teams they root for, the newspapers they read, their alcoholic beverage of choice, or the charity organizations they support. This source of data is not only extensive but also publicly available at the individual Twitter user level. We use these data to identify a brand's political affiliation and its polarization over time, which we call *brand-preference polarization*. For a sensitive topic such as political affiliation, identifying political affiliation and brand preference at scale was not possible prior to the availability of social media data.

We supplement the Twitter data with two additional data sources that capture stated survey-based intentions, and actual product purchases. Overall, we have three data sets:

1. Twitter—The primary data set is publicly available brand followership and political affiliation (based on political party followership) of Twitter users.
2. YouGov—A survey from the marketing research company YouGov in which respondents state their political affiliation and their brand preferences and intentions over time.
3. Nielsen panel data set—This data set allows us to observe the sales of thousands of products at the store and household levels and a proxy for political affiliation based on the election results in the county the consumer or store is located in.

Across these three datasets representing different modes of behavior, we find consistent evidence for brand-preference polarization after the 2016 election, particularly among liberals. A stronger polarization among liberals relative to conservatives after the election of President Trump is consistent with the notion of compensatory consumption (e.g., Mandel et al. 2017). Members of the politically threatened group (liberals) take compensatory actions such as brand followership or purchase of more liberal brands to better establish their threatened political identity.

The remainder of the paper is organized as follows: Section 2 describes the empirical context of our research and details the measures. Section 3 demonstrates the increase in brand-preference polarization based on Twitter followership (Section 3.1), stated brand preferences, and behavior using a large consumer panel from YouGov (Section 3.2) and actual purchase decisions based on Nielsen's retail scanner data (Section 3.3). Section 3.4 describes the evolution of brand-preference polarization after brands have taken a political stand. We discuss implications and further research in Section 4.

2. Data and Methods

2.1. Twitter Data Set

We build a data set of all Twitter users who follow one of 307 major brand accounts that have at least 10,000 followers.[7] We use the term "brand account" to refer to nonpersonal Twitter accounts such as those of companies, sports teams, media outlets, and nonprofit organizations. We collected the data between February 2016, a year before Donald Trump became president of the United States, and December 2018. The data collection includes direct access to monthly level brand and political party followers between February 2017 and December 2018 via the Twitter application programming interface (API), as well as access to followership of these brands at three points in time between February 2016 and February 2017 via https://archive.org/web/.[8] This collection of longitudinal data of brand and political account followership allows us to assess brand-preference polarization surrounding the 2016 election. We restrict the analysis to Twitter users who follow either the Democratic (DEM) or the Republican (GOP, short for "Grand Old Party") Twitter accounts and who do not simultaneously follow both accounts.[9]

To make sure that we keep political affiliation constant and only examine intertemporal variation in brand preferences, we focus the analysis on 176,386 users (95,474 Democrats and 80,912 Republicans), with 4,586,036 user-month observations, who followed one of the two political parties in October 2016 (preelection) and continued following the same political account until the end of 2018 (postelection). To make sure we are using active Twitter users, this sample includes users who follow at least three brands in the first time period (February 2016) and adopted or dropped more than one brand over the entire observation window of 35 months.[10] Users in the data follow, on average, 18.04 brand accounts (sd = 16.11).

2.2. Measure of Political Affiliation

Before investigating whether brands became more polarized over time, we need to establish the measure of brand-preference partisanship and map brands according to their political affiliation. To measure the brand-preference partisanship, we look at the joint followership of a brand and a political account by an individual (Culotta and Cutler 2016). We use the measure of *Lift Preference Partisanship* (*LPP*) to control for variation in the number of followers across brands b and political accounts p:

$$Lift\_Preference\_Partisanship_{bp}(LPP_{bp}) = \frac{P(b \cap p)}{P(b) \times P(p)}, \quad (1)$$

where $P(b)$ is calculated by dividing the total number of brand b's followers by the number of account followers in the data. We calculate the probability of following a political account p, $P(p)$ and the joint probability of following a brand and a political account $p(b \cap p)$ in a similar manner. The lift measure is similar to the Jaccard index, but the denominator in the lift measure is the likelihood of the two events occurring by chance as opposed to their union. Intuitively, the lift measure is the ratio of the likelihood of cofollowing a brand and a political account to the likelihood of following both accounts independently. We further normalize the lift preference partisanship measure such that it sums to 1 across the two political parties, as follows:

$$Relative\_Lift\_Preference\_Partisanship_{bp}(RLPP_{bp}) = \frac{LPP_{bp}}{LPP_{bp(\mathrm{GOP})} + LPP_{bp(\mathrm{DEM})}}. \quad (2)$$

Using the *RLPP* measure, we can score brands on their political affiliation. We developed a publicly available API to provide researchers and interested readers easy access to the unique Twitter-based brands' political affiliation score (http://www.social-listening.org).

2.3. Validating the Measures of Political Affiliation and Preference Partisanship

One may question the relationship between following a brand or a political account on Twitter and the user's preference or political ideology. Users may follow an account on Twitter for reasons other than preferences, such as to obtain information, because of employment with the company, or for social reasons. Additionally, Twitter users may not be representative of the population of brand consumers. We examine the validity of Twitter followership as a measure of preference partisanship using multiple analyses (see Web Appendix 3 for details):

a. We compare the Twitter political party followership with the political ideology score of Barberá et al. (2015).

b. We compare the brand-preference partisanship measures to the stated brand preferences of a representative consumer panel administered by YouGov.

c. We relate the measure of brand political affiliation to political donations made by these brands.

d. For media brands, we compare the preference partisanship for media outlets with the political bias ratings of media outlets according to the Media Bias/Fact Check website.

In all comparisons, we find that the political ideology and brand preferences as measured by Twitter followership are highly correlated with external measures of political affiliation and brand preferences from different sources ($0.24 < \rho < 0.64$); see Web Appendix 3 for details.

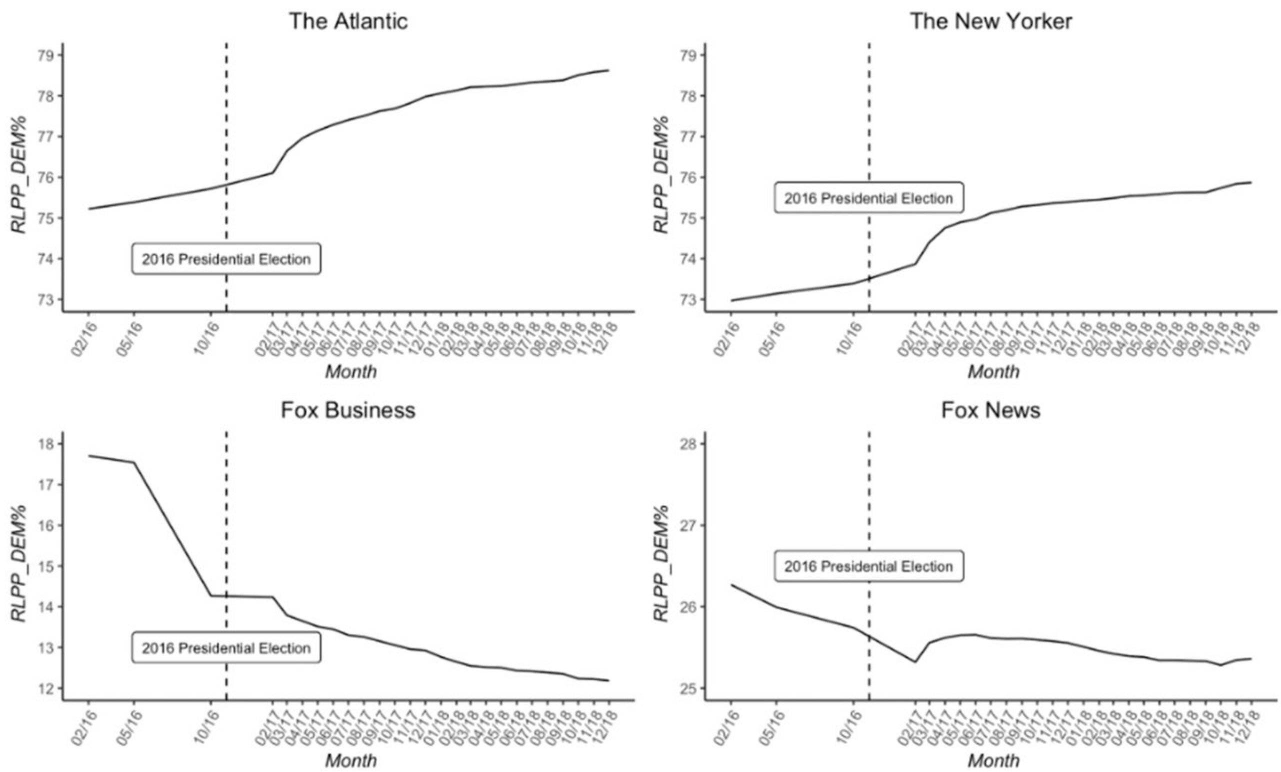
3. What Happened to Brand-Preference Polarization over Time?

3.1. Brand-Preference Polarization in Social Media (Twitter)

A pattern discussed heavily in public media following the 2016 election has been the increased polarization between conservatives and liberals (Gentzkow 2016), particularly driven by the liberal side.[11] This polarization may have spilled over to preference partisanship. That is, liberal (respectively, conservative) individuals may have developed stronger preferences for more liberal (respectively, conservative) brands following the 2016 election. Similarly, brands that had a majority of liberal (respectively, conservative) followers may have become even more liberal (respectively, conservative). Observing the brand-preference partisanship (*RLPP*) over time allows us to assess whether and which brands exhibit stronger polarization after the 2016 election. Indeed, a look at media sources' Twitter accounts clearly highlights the increase in postelection political polarization. As can be seen in Figure 1, Democratic media outlets such as the *New Yorker* and the *Atlantic* became more Democratic, as measured by the political affinity of their followers, after the 2016 election. On the other hand, the political affiliation of the followers of Republican outlets such as Fox News and Fox Business became more Republican (or stayed stable). These exemplary figures suggest an increasing preference polarization after the 2016 election—particularly for Democratic media outlets. Apart from the major event of the election itself, another possible reason for an increase in polarization can be when a brand takes a political action that may affect its follower base. As can be seen in Figure 2, brands that took a political stand (e.g., Nike and Nordstrom) indeed saw a significant shift in the political affiliation of their Twitter follower base after the actions (see also Section 3.4).

To examine this polarization pattern more systematically, and at the consumer level, we analyze the change of the Democratic political affiliation (*RLPP_DEM*) of the users' Twitter "brand basket" (the set of brands each user follows) over time. Specifically, we calculate

Figure 1. The Evolution of Democratic Political Affiliation (*RLPP_DEM*) of Media Outlets



the political affiliation of the brand basket that user i follows in month m as

$$RLPP\_DEM\_Basket_{im} = \frac{\sum_{b=1}^{N_{im}} RLPP\_DEM_b}{\sum N_{im}}, \qquad (3)$$

where N_{im} is the number of brands followed by Twitter user i in month m. To focus on the change in brands that a user follows, as opposed to the change in the brand's political affiliation, in this analysis we hold the political affiliation of the brands constant by calculating the $RLPP\_DEM_b$ for each brand in the first period (February 2016).

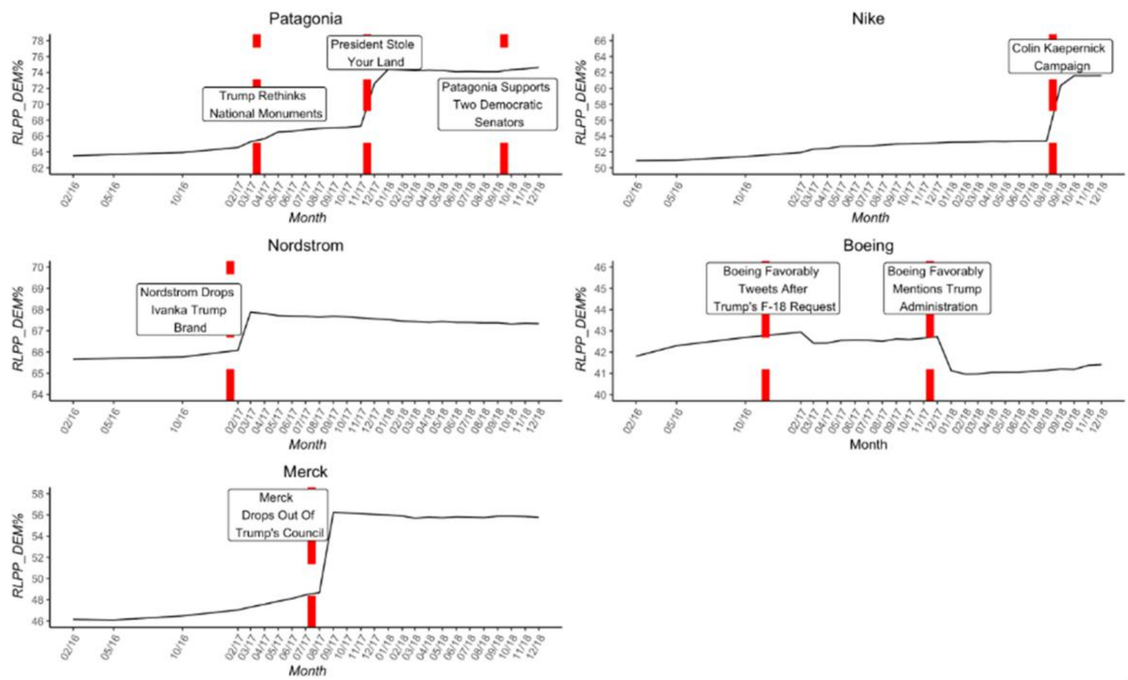
Twitter users vary significantly in the political affiliation of their brand basket. Across users, the *RLPP_DEM_Basket* ranges from 6.65% to 87.45%. Figure 3 shows the evolution of the average Democratic basket (*RLPP_DEM_Basket*) of DEM account and GOP account followers over time.[12] Before the 2016 election (under the Obama administration), the basket of brands followed by both Democratic and Republican Twitter users became more Republican, meaning we observe polarization of conservatives but not liberals. However, after the 2016 election, we see a reversal in this pattern for Democrats, where the basket of brands followed by Democratic Twitter users became more Democratic, demonstrating an increasing polarization after the 2016 election.

It is entirely possible that political affiliation is correlated with users' demographics. Thus, brand preferences may be correlated with observed and unobserved time-invariant differences between users. To control for such possible confounds, we regress the *RLPP_DEM_Basket* on a user fixed effect, a continuous monthly time trend, and a discrete time trend (= 1 for a period after the 2016 election (December 2016–December 2018) and = 0 for a period before the election (February 2016–November 2016)), as well as the interaction between the time variables and the political affiliation of the user (see Table 1).

If polarization increased after the 2016 election, we would expect to see a significant positive effect for the interaction between the postelection period and the DEM affiliation of the user. Indeed, we find that the brand basket followed by Democratic Twitter users became significantly more Democratic after the 2016 election, confirming increased polarization.[13]

We note that whereas the polarization effect in Figure 3 and Table 1 is statistically significant and robust across different consumer behaviors and data sources, as we show later, it is not large in magnitude. A small effect size is to be expected for several reasons. First,

Figure 2. (Color online) The Evolution of Democratic Political Affiliation (*RLPP_DEM*) for Brands That Acted Politically



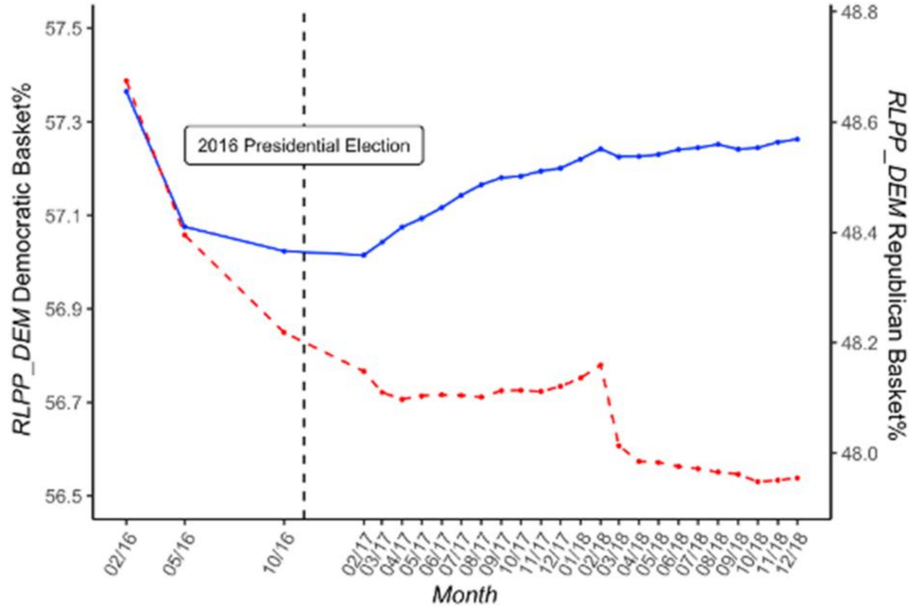
users adopt and drop accounts on Twitter at a fairly low rate. Additionally, given inertia in brand purchases (Dubé et al. 2010), it would be surprising if an exogenous and seemingly unrelated event such as an election were to have a large effect on Twitter brand followership. Indeed, as we can see in Figure 2, we find stronger polarization effects for specific brands that have taken a more explicit and direct political stand.

To get a better sense for the magnitude of the polarization effect, and whether the polarization is asymmetric across the followers of the two parties, we examine the change in the number of Democratic and Republican brands that a user followed over time. We define a Democratic (respectively, Republican) brand as having a *RLPP_DEM* > 50% (respectively, *RLPP_DEM* < 50%). Consistent with the results in Table 1, after the 2016 election, Democrats started following Democratic brands at a faster rate than their adoption of Republican brands and at a faster rate than Republicans adopted Democratic or Republican brands (see Figure 4). On average, Democrats added 4.96 Democratic but only 2.15 Republican brands in the two years following the 2016 election. Republicans, on the other hand, adopted new Democratic and Republican brands at an approximately equal rate (2.96 Democratic and 2.80 Republican brands). Thus, the change in brand followership by users from the two sides of the political spectrum is quite substantial (see Web Appendix 7 for statistical analyses of the results in Figure 4).

The stronger increase in brand-preference polarization for liberals compared with conservatives after the 2016 election and the reversal of the observed brand-preference polarization for Democrats between the Obama era (prior to the 2016 election) and the Trump era (post-2016) in Figure 3 are consistent with the mechanism of compensatory consumption. Past literature has shown that consumers can use the acquisition and consumption of products as a method of self-repair to combat identity threats following an event that triggered a threat to their identity. This mechanism is known as compensatory consumption (Gao et al. 2009, Gal and Wilkie 2010, Cutright et al. 2011, Kim and Rucker 2012, Mandel et al. 2017). Identity threats can arise from individual threats (e.g., a threat to one's intelligence), interpersonal threats (e.g., feeling less powerful compared with others), or group-level threats (e.g., a threat to an individual's religious beliefs; Mandel et al. 2017). A common strategy to cope with such threats is the acquisition, consumption, and display of—or simply the thought of—products that signal success in the threatened domain (Rustagi and Shrum 2019). Compensatory consumption has been shown for a variety of domains such as threats to one's masculinity, intelligence, power, personality, freedom, and status but thus far not to political ideology. In a related work, Long et al. (2018) show that partisan identity threats can lead to greater partisan media selectivity.

Focusing on the 2016 election, liberals faced a threat to their political identity after the unexpected election of Donald Trump, which they possibly compensated for by stronger support for liberal-oriented brands and growing activism (Green 2018).[14] The finding that

Figure 3. (Color online) The Evolution of the Democratic Political Affiliation (*RLPP_DEM_Basket*) of the User Brand Basket over Time for DEM and GOP Twitter Followers



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

liberals consumed media sources, supported nonprofit organizations, and even purchased commercial brands that would help to offset the threat to their identity is consistent with the notion of compensatory consumption (Rucker and Galinsky 2013).

In addition to the consumer-based compensatory consumption explanation, brand assimilation can serve as an alternative explanation for the observed results. Specifically, under this explanation, brands may try to attract more Democrat or Republican customers and therefore change their political affiliation over time. In Section 3.3 we demonstrate the brand-preference polarization effect in the context of supermarket purchases, controlling for brand availability in different geographical markets, thus making the brand-assimilation explanation less likely.

Table 1. Political Affiliation User Basket Pre- and Postelection, According to Twitter Data

Variable	DV = *RLPP_DEM* (in %) Coef. (se)
Post-Election Dummy	−0.164*** (0.011)
Month	−0.011*** (0.001)
Post-Election Dummy × *DEM*	0.036*** (0.013)
Month × *DEM*	0.019*** (0.001)
Constant	53.155*** (0.008)
N	4,586,036
N_{users}	176,386
R^2_{overall}	0.2942

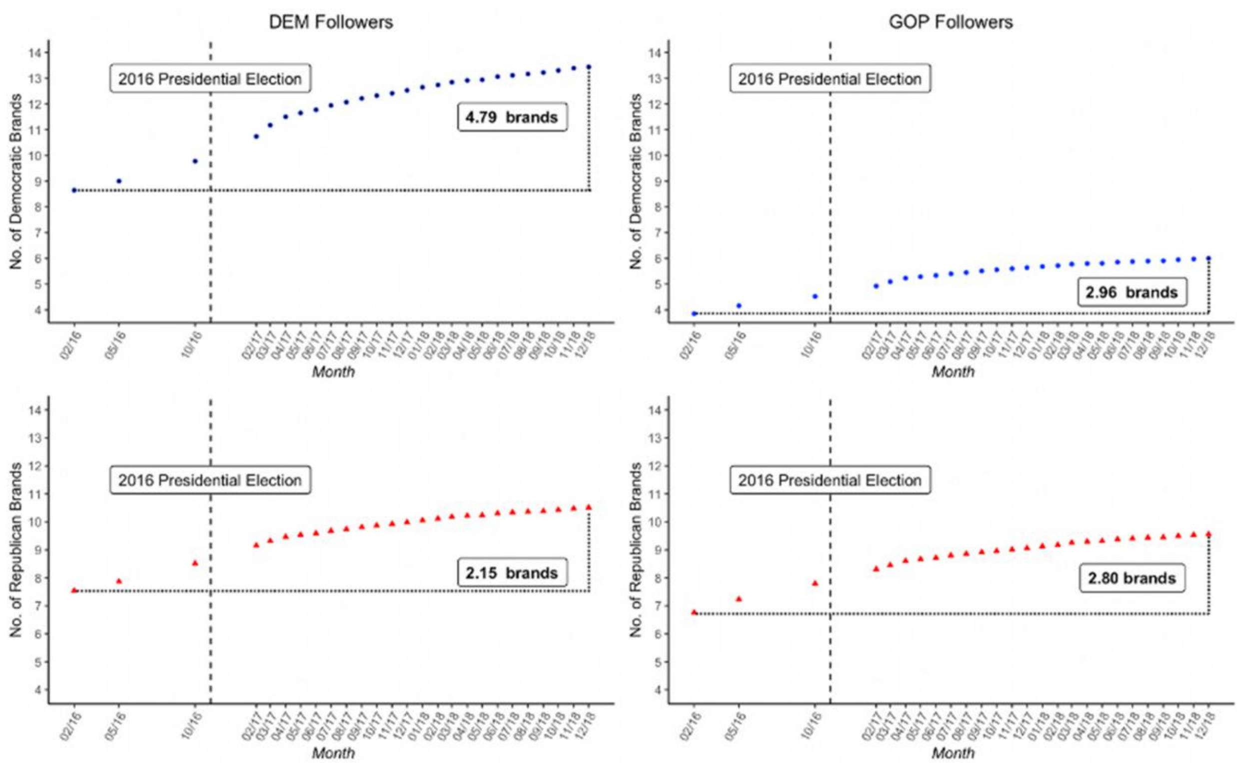
Notes. User fixed effects included. Standard errors are clustered at the user level. The political affiliation of a user is captured by the user fixed effect. *Month* is a variable that captures the linear year-month time trend. DV, dependent variable.
$^{***}p < 0.01$.

3.2. Brand-Preference Polarization in Stated Preference (YouGov)

In this section, we validate and extend the findings from Section 3.1 by investigating the degree to which the increased polarization after the 2016 election manifests also in terms of brand-stated behavioral intentions (YouGov BrandIndex). The YouGov BrandIndex is a daily survey that asks panelists to evaluate brands on dimensions such as consideration, purchase likelihood, ownership, and word of mouth (WOM). We have access to daily brand evaluations of a representative U.S. panel from January 2016 to December 2018.

This data set helps extend the Twitter analysis in several ways. First, whereas the Twitter data set may suffer from self-selection, the YouGov panel uses a representative sample of the U.S. population. Second, this data set complements the measure of brand preference based on Twitter brand account followership with stated brand consideration, willingness to buy, brand ownership, and WOM intentions. Third, YouGov directly measures panelists' political affiliation. Specifically, when panelists sign up to the platform, they indicate their political affiliation (Democrat, Republican, Independent, or other/not sure). In the sample, 92% of the panelists stated their political affiliation. At certain

Figure 4. (Color online) Number of Democratic and Republican Brands Followed over Time by Party Affiliation



Notes. The left panel depicts the evolution of the number of brands followed by Democratic Twitter users over time: the upper left graph shows the number of Democratic brands followed, and the lower left graph shows the number of Republican brands followed. Similarly, the right panel depicts the evolution of the number of brands followed by Republican Twitter users over time: the upper right graph shows the number of Democratic brands followed, and the lower right graph shows the number of Republican brands followed. The vertical dotted line marks the 2016 presidential election.

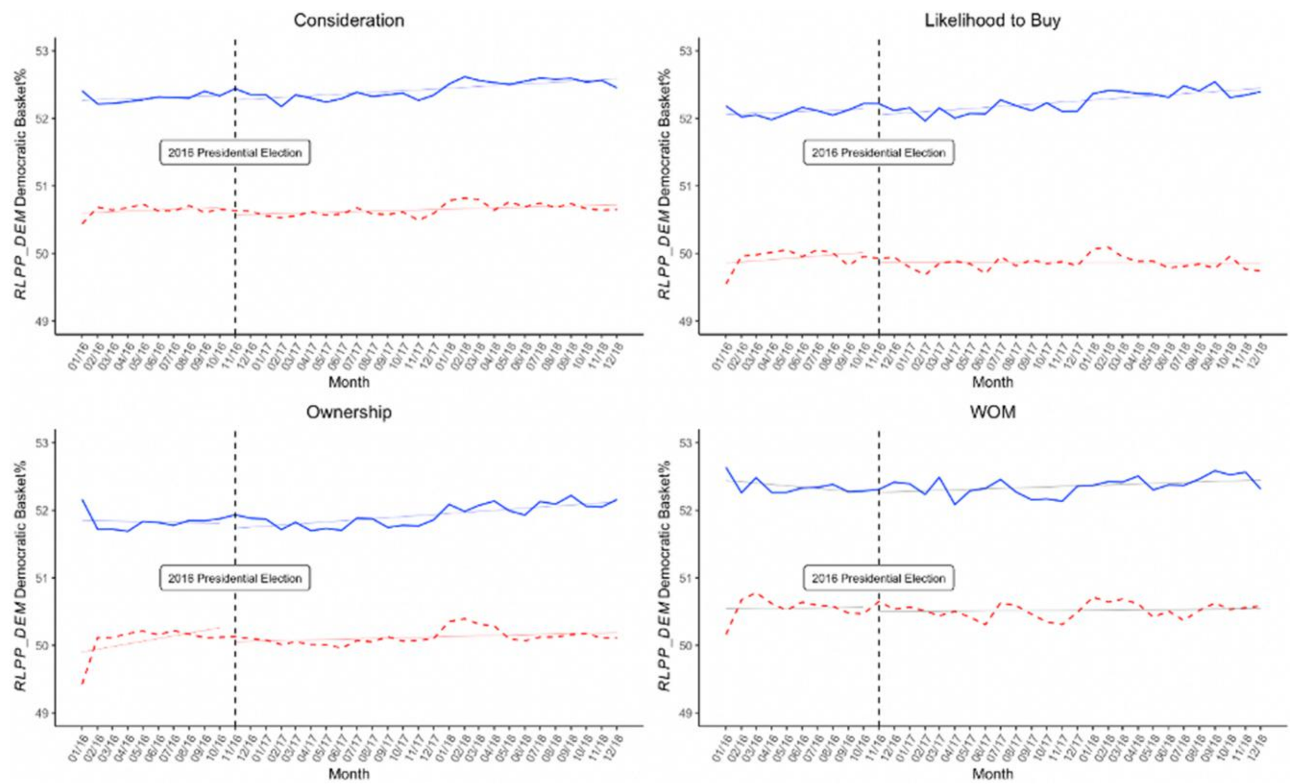
time periods panelists have the opportunity to update their demographic information. Similar to the Twitter analysis, we exclude participants who changed their political affiliation during the data period.

In each survey, panelists are randomly assigned to a single product category from a set of 42 categories like beverages, dining, apparel, travel, and skincare products. The assignment is done based on a quota system, so every category on every given day is nationally representative. Panelists first select the brands that they are aware of within the product category from a list of up to 40 brands presented to each respondent in each survey. They then answer the survey only for the brands they are aware of. In total, we observe 1,308 brands that were presented to panelists in every month throughout the data period. Panelists may participate in the survey at most once a week and be surveyed in the same product category at most once every 77 days. We limit the analysis to panelists who identify as Republican or Democrat, did not change their political affiliation during the data period, and responded to the survey at least once before and after the 2016 election. Similar to the Twitter analyses, the unit of analysis is the "basket" of brands evaluated by each panelist in each month. We only consider brands that were included in the survey throughout the data period. On average, a panelist is observed in 15 of the 36 months of the observation window (sd = 11).

For each panelist/month, we calculate the political affiliation of the monthly panelist basket, meaning the political leaning of the set of brands evaluated by the panelist in a specific month, and control for panelist fixed effects and category dummies. To score brands on their political affiliation, we first calculate the *RLPP_DEM* of each of the 1,308 brands in the data based on stated brand ownership and political affiliation in the first month of the data (January 2016). Recall that we keep the political affiliation of the brand and panelist constant throughout the analysis period. Similar to Equation (3), we assess the political affiliation of a monthly panelist basket by calculating the average of the *RLPP_DEM* of brands that participants indicate they (1) consider, (2) are likely to buy,[15] (3) own, and (4) share WOM in a particular month (see Web Appendix 8 for the survey questions).

Figure 5 shows the model-free evidence of the evolution of the panelist monthly baskets for Democrat and Republican panelists over time. The figure offers

Figure 5. (Color online) The Evolution of the Democratic Political Affiliation (RLPP_DEM_Basket) of the User Brand Basket over Time for Brand Consideration, Likelihood to Buy, Ownership and WOM. Based on the YouGov BrandIndex Survey



Notes. The blue (solid) lines show the evolution of the Democratic basket of Democrats, and the red (dashed) lines show the evolution of the Democratic basket of Republicans. The grey lines show the linear trend line of each graph before and after the 2016 election. The vertical dashed line in each graph indicates the month the 2016 presidential election took place.

several relevant observations. First, for all four behaviors, as expected, Democratic panelists are more likely to prefer Democratic brands (higher *RLPP_DEM*) than are Republican panelists. Second, and more important, we see increased polarization following the 2016 election. For all behaviors, the gap between the political affiliation of the basket of brands of Democratic and Republican panelists has increased since the 2016 election. Third, this increase is mainly driven by the basket of Democratic panelists becoming more Democratic on all four behaviors. Finally, comparing the slopes of the change in the basket before and after the 2016 election, we see an increase in slope for Democratic panelists for all four behaviors-for two of the four behaviors, we even see a trend reversal around the 2016 election. These patterns are consistent with the notion of compensatory consumption among liberals, with polarization after the 2016 election being mainly driven by the behavior of liberals in the data.

Building on the model-free evidence indicating an increasing polarization for Democratic baskets after the 2016 election, and similar to the Twitter analysis, we regress the monthly political affiliation of the basket of brands of panelist i in month m ($RLPP\_DEM_{im}$) on a postelection dummy and a dummy variable that captures the month of the year[16] and also on the interaction between the panelist's political affiliation and the time variables. The regression controls for both panelist fixed effects and product category dummies. Similar to the Twitter analysis, we find an increase in polarization for all four stated behaviors (see Table 2). These results support the Twitter polarization findings and extend them to additional measures of brand preference and intention among a representative sample of consumers, with a stated and comprehensive measure of political affiliation.

3.3. Brand-Preference Polarization in Actual Purchase Decisions (Nielsen Retail Scanner)

To go beyond Twitter account followership or stated willingness to buy, we examine possible brand polarization in actual purchase decisions using purchase data from the Nielsen Retail Scanner Data, which reports store-level sales of grocery products across the United States.

The Nielsen Retail Scanner Data includes weekly sales, aggregated to a monthly level, for 27,043 brands[17] sold in 27,502 stores between January 2016 and December 2018. We use the brands' sales in 2015 to assess political brand affiliation and the data from 2016 to 2018 to assess brand-preference polarization. To separate the effect of demand from supply (product availability), we only consider in this analysis the 27,043 brands that were sold at least once in the store in each of the 36 months of the data period. Thus, the basket of brands sold could vary across stores but not within a store over time. The mean number brands per store is 1,132 brands.

Similar to the $RLPP\_DEM_b$ in the Twitter and YouGov analyses, in this analysis we calculate the brand's political affiliation (BPA_DEM_b) by the weighted average of the brand's sales across stores between January and December 2015, weighted by stores' county-level political affiliation:

$$BPA\_DEM_b = \frac{\sum_s Q_{sb2015} \times DEM\_voting\_result_s}{\sum_s Q_{sb2015}}, \qquad (4)$$

where Q_{sb2015} is the quantity of brand b purchased in store s in 2015, and $DEM\_voting\_result_s$ is the share of the 2016 election votes for Hillary Clinton out of votes for Hillary Clinton and Donald Trump in the store's county (we observe stores in 2,449 counties). Having a brand political affiliation (BPA) for each brand in the purchase data set, we define the political affiliation of the sales in store s in month m by the products purchased in a store in each month weighted by their BPA:

$$Share\_DEM_{sm} = \frac{\sum_{b=1}^{N_s} Q_{smb} \times BPA\_DEM_b}{\sum_{b=1}^{N_s} Q_{smb}}, \qquad (5)$$

where Q_{smb} is brand b's quantity sold in store s in month m, and N_s is the number of brands sold in store s. As in the Twitter analysis, to separate changes in consumers' preferences over time from changes in brands' political affiliation, we hold brands' political affiliation (BPA_DEM_b) constant based on their sales in 2015. The measure of store sales political affiliation ($Share\_DEM$) captures how Democratic the brands sold in the store are. Given that the political affiliation of brands is held constant as of 2015, the only way for the measure of the political affiliation of the store's sales to vary over time is through variation in the brand mix sold in the store. Thus, a store can become more (respectively, less) Democratic over time if the share of Democratic brands purchased in the store increases (respectively, decreases).

Similar to the Twitter and the YouGov analyses, we regress the political affiliation of the store sales in each month ($Share\_DEM_{sm}$) on a postelection dummy (and a continuous monthly time trend) and on the interaction between the voting result in the store's county and the time variables. We also control for the average price of the brands in a store, mean-centered at the brand level, and for store fixed effects, which capture any time-invariant store-specific effects such as the demographics and the political affiliation of the store's buyers.

The results in Table 3 demonstrate a positive and significant interaction between the postelection dummy and the counties voting for Hillary Clinton ($\beta = 0.0107$, $p < 0.01$), indicating that in stores located in Democratic areas, the sales became significantly more Democratic after the 2016 election. This supports the observations of increasing polarization in preferences found in the Twitter and YouGov analyses, this time reflected by actual purchases.[18]

Table 2. Political Affiliation of Survey Panelist Baskets Pre- and Postelection, According to YouGov BrandIndex Survey

	DV = *RLPP_DEM* (in %)			
Variable	*Consideration* Coef. (se)	*Likelihood to Buy* Coef. (se)	*Ownership* Coef. (se)	*WOM* Coef. (se)
Post-Election Dummy	0.1465***	−0.1820***	−0.0964***	−0.1766***
	(0.0191)	(0.0275)	(0.0219)	(0.0335)
Post-Election Dummy × DEM	0.1399***	0.2463***	0.0816***	0.1035**
	(0.0258)	(0.0370)	(0.0298)	(0.0450)
Constant	51.63***	51.20***	51.20***	51.79***
	(0.0260)	(0.0350)	(0.0296)	(0.0459)
Month	✓	✓	✓	✓
Month × DEM	✓	✓	✓	✓
N	777,020	739,707	667,206	480,061
$N_{\text{panelists}}$	48,655	47,583	45,920	38,603
R^2_{overall}	0.1050	0.0756	0.0797	0.0626

Notes. Panelist fixed effects and category dummies are included. Panelists' political affiliation is captured by the panelist fixed effect. Standard errors are clustered at the panelist level. The number of survey panelists differs among the four outcome variables, as panelists can skip questions. *Month* is a dummy variable that captures the month of the year. DV, dependent variable.
$^{**}p < 0.05$; $^{***}p < 0.01$.

The interaction effect in Table 3 (the first column) may seem small, but keep in mind that we are averaging more than 27 thousand brands in total and an average of 1,132 brands per store month. To better quantify the increase in the sales of Democratic brands in Democratic counties following the 2016 election, we run the same regression as in the first column in Table 3 and replace the dependent variable with the sales of the store weighted by its brands' binary Democratic affiliation (second column in Table 3):

$$Sales\_DEM_{sm} = \sum\nolimits_{b=1}^{N_s} Q_{smb} \times I(BPA_{DEM,b} > 0.5). \quad (6)$$

We see a significant and substantial increase in sales for Democratic brands after the 2016 election in Democratic counties. For example, the predicted change in monthly sales of Democratic brands in a store in Franklin, Massachusetts (70% Clinton to Trump votes in the 2016 election), increased postelection by (3,880.25 × 0.7) + 331.9 = 3,048 units relative to an increase of only (3,880.25 × 0.3) + 331.9 = 1,496 in Jackson, Mississippi (30% Clinton to Trump votes in 2016), on top of the continuous time trend.

Admittedly, the measure of political affiliation in the Nielsen analysis may combine both demand and supply effects, as it is based on sales of the brands in 2015 across counties. To test the validity of the geography-based Nielsen proxy for political affiliation, we compare the correlations between the political affiliation from the Nielsen data (BPA_DEM_b) and the Twitter measure of brand political affiliation for a subset of brands that overlap between the two data sets. We find a substantial and significant correlation between the two measures ($n_{\text{brands}} = 281$, $\rho = 0.3515$, $p < 0.01$). We also rerun the analysis in Table 3 using the subset of brands for which we also have access to brand political affiliation in the Twitter data. For this subset we compare results using the Nielsen and the Twitter proxy of political brand affiliation—the results hold when using either proxy. This serves as a robustness test for the findings, in terms of both the sample of brands and the way we measure brand political affiliation (see Web Appendix 9).

The analysis so far demonstrates an increase in the sales of Democratic brands in Democratic counties relative to Republican counties after the election in 2016. Recall that we only look at brands that were sold in the store throughout the three years of the data period to separate demand effects from supply or product availability. We also control in all models for the average prices of Democratic brands. We now turn to look at possible political polarization in the supply of brands (e.g., availability or pricing). First, to test if sellers have differentially changed the price of Democratic and Republican brands over time, we replicate the regressions in Table 3, this time with the dependent variable being the average price of brands in stores weighted by their Democratic political affiliation:

$$Price\_DEM_{sm} = \frac{\sum_{b=1}^{N_s} Price_{smb} \times BPA\_DEM_b}{\sum_{b=1}^{N_s} BPA\_DEM_b}. \quad (7)$$

A significant effect of the interaction between the postelection dummy and the *DEM_voting_result* would suggest that the store changed its price based on the political affiliation of the store's county. Although the result in the third column of Table 3 shows a decrease in the price of Democratic brands in Democratic counties post the election, this decrease is only marginally statistically significant. This offers further evidence that the increase in demand for Democratic brands in stores located in Democratic counties is unlikely to be driven by a lower price for Democratic brands.

Table 3. Political Affiliation of Store Sales Pre- and Postelection by the County's Political Affiliation, According to Nielsen Retail Scanner Data

Variable	$Share\_DEM_{sm}$ Coef. (se)	$Sales\_DEM_{sm}$ Coef. (se)	$Price\_DEM_{sm}$ Coef. (se)
Post-Election Dummy	−0.0177*** (0.0013)	331.90* (183.82)	0.0130*** (0.0013)
Month	0.0021*** (0.0001)	77.49*** (14.22)	0.0040*** (0.0001)
Post-Election Dummy × DEM_voting_results	0.0107*** (0.0024)	3,880.25*** (357.86)	−0.0042* (0.0025)
Month × DEM_voting_results	−0.0002 (0.0002)	−904.12*** (30.16)	0.0012*** (0.0002)
Price Control	0.0812*** (0.0043)	−5,060.99*** (624.74)	NA^
Constant	52.62*** (0.0010)	112,270.90*** (140.60)	4.92*** (0.0004)
N	990,072	990,072	990,072
N_{stores}	27,502	27,502	27,502
R^2_{overall}	0.18	0.04	0.002

Notes. Store fixed effects are 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 are clustered at the store level. ^, price control is irrelevant for the Price_DEM regression.
$^*p < 0.1$; $^{***}p < 0.01$.

To examine whether stores changed their product availability based on the political affiliation of their customers following the 2016 election and to further investigate the explanations of brand assimilation versus compensatory consumption, we relax the assumption that a brand needs to be sold in every month in the store to be included in the analysis and look at all brands that were sold at least once in the store in the data period ($n_{\text{brands}} = 76{,}441$). We then calculate the political affiliation of the brands available in the store in each month as

$$Availability\_DEM_{sm} = \frac{\sum_{b=1}^{N} I(Q_{smb} > 0) \times BPA\_DEM_b}{\sum_{b=1}^{N} I(Q_{smb} > 0)}, \tag{8}$$

where N is the number of brands in the data. In this measure, a brand is available in the store if it was sold at least once $I(Q_{smb} > 0)$ in the month in the store. We replicate the regressions in Table 3 with the dependent variable being the availability measure in Equation (8). We find a negative and significant effect for the interaction between the postelection dummy and the *DEM_voting_result* in the store's county on the availability of Democratic brands (see Table 4). This suggests that, counter to the demand effect, the availability of Democratic brands decreased in Democratic counties, and hence the increase in polarization is likely driven by a change in consumer demand and not a change in the availability of brands.

The analysis of the Nielsen Retail Scanner Data allows us to investigate the polarization of store sales across geographical areas. However, we do not know whether the increase in the sales of Democratic brands in Democratic counties is driven by Democratic consumers buying a larger variety of Democratic brands or a higher quantity of the Democratic brands they already purchase. To disentangle the effect of brand choice from quantity purchased, we complement the Nielsen Retail Scanner data with data from the Nielsen Homescan Consumer Panel before and after the 2016 election. We focus on the category with the widest spread of political affiliation across brands—soft drinks.

The results show that the effect reported at the store level replicates at the household level focusing on 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 an increase in the unique Democratic brands purchased by Democratic households and not by an increase in the quantity purchased of these brands (see details in Web Appendix 10).

Overall, the findings from the analysis of the Nielsen purchase data are consistent with the previous Twitter and YouGov results. Moreover, this analysis demonstrates that preference polarization goes beyond brand preferences in terms of Twitter followership and behavioral intentions to actual purchase behavior. We are also able to disentangle whether the effect is driven by an increasing supply of Democratic brands or consumers' demand for these brands.

Taking all this evidence together across multiple data sets using different political and brand affiliation metrics—brand following on Twitter, stated preferences, and actual purchases—we identify brand-preference polarization in the United States after the 2016 election. This polarization is primarily driven by increased preferences of Democratic consumers for Democratic brands.

3.4. Polarization for Brands Taking a Stand

Following the 2016 election, there was an upswing in brands publicly opposing Donald Trump's policies,

Table 4. Political Affiliation of Available Products in Stores Pre- and Postelection by the County's Political Affiliation, According to Nielsen Retail Scanner Data

Variable	DV = *Availability of Democratic Brands* Coef. (se)
Post-Election Dummy	0.0002*** (0.000)
Month	0.0001*** (0.000)
Post-Election Dummy × *DEM_voting_result*	−0.0006*** (0.000)
Month × *DEM_voting_result*	−0.0001*** (0.000)
Price Control	−0.0004*** (0.000)
Constant	0.5334*** (0.000)
N	990,072
N_{stores}	27,502
R^2_{overall}	0.0867

Notes. 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 are clustered at the store level. DV, dependent variable.

***$p < 0.01$.

such as Nordstrom discontinuing Ivanka Trump's product line. Many brands, such as Google or the *New York Times*, have been attacked by Donald Trump.[19] Indeed, Figure 2 reveals that involvement in such political activity was often associated with a large change in the brand's RLPP. For example, looking at Patagonia, we see a substantial increase in its *RLPP_DEM* after the brand took a stand against Donald Trump in December 2017 ("The President Stole Your Land"[20]). Similarly, for Merck, which was part of Donald Trump's advisory council, we observe an increase in its *RLPP_DEM* once the company left the council. We see the opposite polarization for brands that have supported Donald Trump—although these events are rarer. For example, Boeing exhibited a decrease in its *RLPP_DEM* when it supported Donald Trump in a tweet.

To more systematically explore whether the increased polarization following the 2016 election is related to brands actively or passively taking a political stand, we conducted an analysis for $n = 101$ brands that took an action during the data period. We find that only brands that took an action against Donald Trump became significantly more Democratic (see Web Appendix 11). Because brands endogenously choose to take an action, these results should be interpreted as correlational rather than causal. We leave for future research a causal investigation of the effect of such actions on the brand political affiliation.

4. Conclusion

This paper illustrates that the U.S. political divide and polarization extend to consumers' brand preferences. We find increased political polarization in Twitter brand followership, stated behavioral intentions, and even actual purchases after the 2016 presidential election. Interestingly, we find a stronger polarization for liberals, which can be attributed to the mechanism of compensatory consumption. This finding is in line with the growing activism of liberals after the 2016 election. We also show that the polarization is driven by an increasing demand rather than by an increasing supply of Democratic brands after the election. Moreover, the results suggest that brands taking a political stand can take control of their political polarization. Although we provide robust evidence across multiple consumer behaviors and data sets for an increasing polarization in consumers' brand preferences after the 2016 election, we acknowledge that the analyses do not causally establish the drivers underlying the political polarization in consumption. We encourage future research to investigate this important topic.

A notable contribution of our work is demonstrating the value of using publicly available social media data both to infer consumers' brand partisanship and to track brand-preference polarization. Such an endeavor was effortful, costly, and unscalable in the past. However, one may question the generalizability of Twitter data to infer consumers' preferences. Accordingly, we validate the findings from Twitter using stated preference data and actual purchases. These additional data sets also offer us the opportunity to capture preference and political affiliation more broadly and hence further test the robustness of the results. We encourage future research to explore how preference partisanship can be extracted from other data sources such as e-commerce data.

Future research could also examine the relationship between political affiliation and individuals' opinions regarding other societal issues such as climate change and sustainability (Culotta and Cutler 2016). The recent U.S. presidential election in 2020 offers yet another shift in political power and thus a great opportunity to further investigate the polarization of brand preferences and its underlying mechanisms.

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The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Endnotes

[1] See the results of the Pew Research Center survey at http://www.people-press.org/interactives/political-polarization-1994-2017 (accessed May 1, 2022).

[2] Hereafter, we refer to this simply as the 2016 election.

[3] See https://www.investors.com/politics/editorials/pew-research-center-study-shows-that-democrats-have-shifted-to-the-extreme-left/ (accessed May 1, 2022) and https://assets.pewresearch.org/wp-content/uploads/sites/5/2017/10/05162647/10-05-2017-Political-landscape-release.pdf (accessed May 1, 2022).

[4] See http://www.washingtonpost.com/wp-dyn/articles/A218-2004Dec14.html (accessed May 1, 2022).

[5] We interchangeably use "liberals" and "Democrats" as well as "conservatives" and "Republicans" to reflect the two sides of the political spectrum.

[6] See https://www.technologyreview.com/s/609229/how-tweets-translate-into-votes (accessed May 1, 2022).

[7] We selected brands tracked by Young & Rubicam's Brand Asset Valuator and Interbrand, which track brands that are of high relevance to consumers.

[8] Web Appendix 1 describes the details of the data extraction.

[9] We exclude users who follow both the DEM and GOP accounts (24%), because these users may be swing voters, political enthusiasts, or users who wish to learn about the opinions voiced by the

opposite political side. We removed suspect bot accounts using the Botometer algorithm (see Web Appendix 2 for details).

[10] The results are similar without restricting the number of brands followed in February 2016 and the number of brands adopted or dropped.

[11] See https://www.investors.com/politics/editorials/pew-research-center-study-shows-that-democrats-have-shifted-to-the-extreme-left/ (accessed May 1, 2022) and https://assets.pewresearch.org/wp-content/uploads/sites/5/2017/10/05162647/10-05-2017-Political-landscape-release.pdf (accessed May 1, 2022).

[12] See Web Appendix 4 for the representation of Figure 3 using the median basket instead of the mean basket.

[13] We find similar results if we define *RLPP_DEM* not only over the LPP of GOP and DEM followers but also over all brand followers, including those with nonpolitical affiliations (see Web Appendix 5 for details). In Web Appendix 6, we further split the GOP followers into those who also follow Donald Trump and those who do not. We also include a group of Donald Trump Twitter account followers who do not follow the GOP. We find the polarization persists across all groups, but GOP supporters show a stronger polarization compared with supporters of only Donald Trump.

[14] See https://www.theatlantic.com/politics/archive/2018/10/poll-shows-activism-highest-among-non-religious-democrats/572674/ (accessed May 1, 2022).

[15] The "likely to buy" question is a "select one" type of question based on the set of brands participants said they would consider, assuming they considered at least one brand.

[16] Because the number of brands being asked about per user in each time period (month) is limited, we only include a month of the year dummy as the control, as every calendar month appears three times in the data.

[17] We aggregate SKUs to a brand level.

[18] We acknowledge that the Nielsen Retail Scanner Data are not fully representative of all U.S. retail chains, as such data are neither a randomly selected sample nor cover all U.S. retail stores. To account for this, we are using store fixed effects.

[19] For a list of brand events, see the Brand Event List in the Supplemental Material.

[20] See https://www.cnbc.com/2017/12/05/brands-and-politics-patagonias-the-president-stole-your-land.html (accessed May 1, 2022).

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