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Awareness of political alignment of Twitter networks: insights from a linked survey.

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A frequently discussed dilemma concerning online media consumption are so-called "echo chambers": is the information environment of Internet users increasingly one-sided due to factors such as homophily and selective exposure? While much research has been devoted to the scope and penetration of echo chambers and the potential effects of counter-attitudinal exposure, there is a research gap when it comes to the perceptions of the Internet users themselves. How do consumers view their information environments and are they aware of how politically slanted those environments are? We argue that such awareness is a core-determinant when evaluating the potential impact of echo chambers on society because awareness of biased information flows enables conscious content selection and is therefore directly linked to the "demand" side of individuals' Internet-consumption. By evaluating a linked survey of a representative U.S. online panel we find that a false consensus effect biases the perceptions that Twitter users have of their information environment. At the same time, political sophistication helps users more accurately determine the political slant of their Twitter network. We discuss the implications of these findings for research and policies on echo chambers.

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INTRODUCTION

On March 17th, 2018, Donald Trump "went on a daylong Twitter tirade, batting out more than 30 tweets that appear to have come from extended immersion in the streams flowing through his account".[1] The New York Times then argues that the president of the U.S. – through reacting and replying to the content presented to him on Twitter – helps to promote white supremacist influencers and conspiracy theories (McIntire et al. 2019). In fact, scientists have long warned of the potential dangers so-called "echo chambers" might pose to democracies (e.g., Sunstein 2009). These situations of relative isolation may emerge from algorithms (Pariser 2011) or via psychological motivations such as selective exposure (Stroud 2014; Frey 1986; Stroud 2010) and homophily (McPherson et al. 2001; Gargiulo and Gandica 2017) but ultimately pose a threat to individuals' perceptions on what is considered *normal*.

The extensive scope of customization options and the vast increase of news-sources on the Internet has been prominently theorized to worsen an already existing problem (Prior 2007; Winneg et al. 2014) and a large body of work has evaluated the existence and penetration of *echo chambers* (e.g., Iyengar and Hahn 2009). The results are mixed, often pointing to audience fragmentation and clustering (e.g., along political lines Barberá 2015; Boutyline and Willer 2016), however, the implications of these kinds of dynamics are not clear as online-media users are also regularly exposed to cross-cutting political content (Yardi and Boyd 2010; Barberá et al. 2015; Bakshy et al. 2012, 2015; Eady et al. 2019).

Targeting the problem from the individual level, online users may change their consumption behavior and tackle this information dilemma via conscious alterations of their subscriptions to news outlets and influencers (see e.g., Bail et al. 2018, for the effect of Facebook-following behavior on political polarization). Many online news outlets have already recognized the possible impact on the demand side of Internet consumption and published articles and tools to sensitize users for the implications of biased news diets (e.g., allsides.com[2]). In this sense, online users – despite psychological mechanisms predicting a more convenient tendency – may consciously opt to e.g. subscribe to news outlets of

[1] `https://www.nytimes.com/interactive/2019/11/02/us/politics/trump-Twitterdisinformation.html`, *Last accessed: 9th December, 2019*

[2] *Last accessed: 9th December, 2019*

opposing opinion and consequently expand the diversity of their news diet. In this project, we aim to evaluate the potential of this path of consumer behavior change.

One requirement for these conscious adaptations – an individual's ability to recognize one's political network slant – has not been studied. In contrast, for example, the perceptions of media quality is already much better understood (e.g. Clayton et al. 2019). Consequently, when talking about the problem of echo chambers, we currently do not know whether Internet users are actually aware of the slant of their online-network and, if they are, which determinants impact this awareness. Prior research on perceptions of social media users also stress the need for a proper evaluation of the relationship between perceptions and reality (e.g. Barnidge 2017). We attribute this research gap to the extensive observational measurements and costly qualitative research that were previously necessary to compare perceptions to behavior (Bernard et al. 1984). In this paper, we instead develop a strategy that leverages social media data as an alternative to accurately model modern media consumption.

This paper specifically takes an important first step towards closing this research gap by showing how U.S. Twitter users perceive their Twitter network in terms of its political composition, which biases these perceptions might be subject to and how these perceptions compare to reality. Relating to our earlier example: while Donald Trump might be aware of the political slant of his Twitter network, how does the average U.S.-citizen fare with regards to the awareness of their online networks' political alignments? We hypothesize that perceptions about networks are biased by a false consensus effect (FCE), i.e. the tendency to overestimate the proportion of persons having similar characteristics as oneself in a population. We then show that in fact, the FCE proves to be a major driver when formulating expectations about one's Twitter network-heterogeneity while political sophistication helps accurately identify one's Twitter network slant.

THEORETICAL BACKGROUND

There is a long-standing insight from previous survey research that self-reported social networks do not necessarily reflect the observed acquaintances, which poses a serious threat to communication research (Corman 1990). Survey participants answer incorrectly and are assumed to hold biased perceptions about their communication behavior. In fact, Bernard et al. (1982) even go so far as to claim that "what people say [about their communication network], despite their presumed good intentions, bears no resemblance to their behavior" (p. 63) stressing the discrepancy between perceived and actual practices. But why do these differences occur and how can they be explained?

Kunda (1990) stresses the importance of the effect an individual's motivation has on the biased search through memory and concludes that people may arrive at conclusions they want to arrive at. The concept of motivated reasoning has found increasing support since it was first introduced and has also already previously been applied to the study of political misconceptions (Flynn et al. 2017) and social media content (Asker and Dinas 2019). One such fallacy is the *False Consensus Effect* (FCE) (Ross et al. 2009) also known as "looking glass perception" (Fields and Schuman 1976) or projection hypothesis (Gunther et al. 2001) which since it was first introduced by Wallen (1943) has found empirical support in numerous applications (see Marks and Miller 1987, for an overview) and is especially relevant for research on contemporary media consumption (see, e.g., Schulz et al. 2018). It postulates that a person projects their opinion onto others and thus will be likely to overestimate the proportion of similar persons in a group or as Fabrigar and Krosnick (1995) describe it:

> "When asked to estimate the proportion of others who possess a particular attitude toward an object, people who themselves hold that attitude generate higher estimates than do people who do not hold that attitude." (Fabrigar and Krosnick 1995, p. 496)

These slanted estimates support people in their view as they are more likely to consider their opinion to be part of an inflated majority. People do not arrive at these self-serving conclusions because they are willing to but because these conclusions seem more plausible (Taber et al. 2001; Kunda 1990). They are mainly driven by two goals: accuracy goals – i.e. people are aware of an effort-accuracy-trade-off and select strategies by considering both the strategies' costs and benefits – and directional goals – i.e. people have the desire to maintain their prior beliefs (Taber et al. 2001; Kunda 1990). We consider the FCE one such possible prior belief which people may uphold. In line with the FCE, we, therefore, hypothesize that the self-reported political alignment of a respondent will impact the perceived share of followed Twitter users. We expect Twitter users to overestimate the share of people with the same opinion as themselves among their Twitter network (H1).

While people require simplifications of reality to cope with complex social structures (Lai 2019), having a good sense of one's surroundings may benefit individuals as they potentially gain an information advantage over others (Janicik and Larrick 2005; Cialdini and Goldstein 2004) or better access to valuable resources (Seo and Ebrahim 2016; Domahidi 2018). In particular, the ability to be aware of the political slant of one's surroundings in the online sphere could be considered an *Internet-skill* (van Deursen and van Dijk 2011) that is of crucial importance in contemporary news- and discussion culture. Internet users need not only be able to find information online (Hargittai 2002) but also should be able to properly evaluate the content they encounter (Hargittai and Micheli 2019) to successfully navigate online resources. Online media consumption is related to political actions (see e.g., Endres 2020, on voting behavior) and conscious and critical usage could potentially lead to more self-deterministic behavior. The advantage of sensitivity to one's surroundings is also highlighted by cases where awareness is being limited or altered by strong biases of resources (Garrett et al. 2016) or via manipulation of the communication environment such as e.g. on social media in China (King et al. 2017) or Russia (Spaiser et al. 2017).

Despite its profound implications for the widely discussed dilemma of echo chambers, awareness of online-network slants or a sense of the political alignment of one's online friends has not been studied extensively to our knowledge. Lai (2019) found that social purposes of social media usage lead to perceptions of larger networks and more diverse connections. Additionally, she relates the frequency of publishing content to perceptions of more diverse social contacts. Levordashka and Utz (2016) analyzed social media users' ability to develop an understanding of their online network. The underlying concept – *ambient awareness* – assumes that social media users learn passively about their contacts by communicating and interacting without an active effort of doing so (Leonardi 2015). For a sample of Twitter users, Levordashka and Utz find a positive relationship between a person's Twitter activity and the knowledge about the characteristics of those users a given person is subscribed to on Twitter. They do not, however, extend their study to the awareness of the political characteristics of the Twitter network. Wojcieszak and Price (2012a) compared perceived and recorded political disagreement collected via an online survey and found that overall perceptions are only weakly related to observations while participants were able to more accurately detect disagreement when participating in discussions on value-laden issues. Additionally, they found that political knowledge correlated with perceptions of disagreement while – contrary to their expectations – participants with extreme opinions reported less disagreement than moderate participants (see also Wojcieszak and Price 2012b). A few complementary insights were provided by Pew Research[3] which gathered information about the normative evaluations of one-sided news diets (Mitchell et al. 2016) and the willingness to adjust one's online resources in case of dissent (Mitchell et al. 2014). There is, to the best of our knowledge, no publication that evaluated online users' ability to recognize the average political alignment of their online network.

Empirical Setting

Twitter is a micro-blogging and social media platform that allows users to subscribe to ("follow") other Twitter users. People will receive updates of published content ("tweets") and reactions to published content of Twitter users they follow (subsequently called "Twitter friends"). Overall, these reactions and tweets in addition to inserted ads from Twitter will make up the "diet" of a Twitter user. Importantly, as these Twitter friends make up the only measurable resource of one's Twitter diet, statements about the characteristics of one's Twitter network will necessarily reflect also the characteristics of one's Twitter diet.

The decision to follow or "unfollow" another account on Twitter is presumably a conscious action. People follow other users because they are e.g. interested in their published content. They unsubscribe from accounts about whom they do not want to be kept updated about or associated with. In both processes, mechanisms such as selective exposure (Stroud 2010) but also the purpose of the Twitter usage may play a role (Lai 2019). Over the course of their usage time, Twitter users accumulate many Twitter friends (avg. = 577.1, median = 148 in our sample) and it seems unreasonable to assume that people are fully aware of every person they are following. As other studies have shown that, when probed in an interview, some connections might come to mind first (Kunda 1990; Litt and Hargittai 2016; Taber et al. 2001) and the imagined network may differ from the actual connections (Kilduff et al. 2008).

[3] `www.journalism.org`, *Last accessed: 9th December, 2019.*

Consciousness gained passively through Twitter activity

For respondents to arrive at valid estimates of the political slant of their Twitter network, they need to be aware of the characteristics of that network. This factual knowledge about others may depend on several factors related to the general activity characteristics of a Twitter user. Social media users passively build awareness of each other through persistent publications of – or reactions to – status updates, thus affecting both senders and receivers of messages (Hampton 2016; Leonardi and Meyer 2014). People who spend more time on Twitter are consequently more knowledgeable about their Twitter network as they receive updates from all their friends and might react to them (Levordashka and Utz 2016). Given that general consciousness about the Twitter network is one condition to then identify the political slant of a Twitter network, we assume that higher activity levels also relate to better awareness of one's political Twitter network slant (H2).

Consciousness through active involvement with politics

To provide a proper estimate of the political alignment of one's Twitter network, respondents not only need to keep track of whom they are following but also need to be able to correctly identify the political leaning of content or, respectively, a Twitter user. But how do our respondents evaluate their network? The process of evaluating one's surroundings stems from the reading of tweets of their Twitter network that appear upon visiting the platform and the inspection of reactions of others to content ("likes" or "retweets"). As a thorough investigation of each Twitter friend at the time of our survey was not possible for respondents, heuristics will play a crucial role in the assessment of their Twitter friends. The "likability heuristic" of Brady and Sniderman (1985) describes one such potential cognitive shortcut when evaluating political issues. A participant may infer political alignment from the other's taken stance on a topic or an action. As an example, we might conclude that a person has a conservative mindset because the person supports increased spending for the military and participated in a pro-Trump protest. However, as Lawrence and Palmer (2002) suggest, the application of this heuristic is limited by levels of political sophistication. In our example, a person needs to know at least who Donald Trump is and whom he represents to make the right conclusions. This sophistication is garnered through e.g. education, political interest and active involvement with the political sphere and news. Consequently, higher levels of political sophistication are associated with a higher probability to detect associations between a range of political beliefs (Sniderman et al. 1991). These conclusions are more likely to be correct with more political sophistication and we therefore assume that people with higher levels of political sophistication will be more likely to identify the political slant of their Twitter network (H3). Table 1 summarizes our hypotheses.

RESULTS

Perceptions Indicators

To evaluate our hypotheses, we analyzed data from a representative linked online survey administered via YouGov[4] to U.S. respondents (n=1339).[5] The data set includes answers to questions distributed in seven waves between April 2018 and March 2019 and merged respondent's Twitter activity with self-referential information about politics, media, and online activity.

TABLE 1. Hypotheses overview

Hypothesis 1	Twitter users overestimate the share of Twitter friends with the same opinion as themselves
Hypothesis 2	Higher levels of Twitter activity are related to higher levels of awareness about the political alignment of one's Twitter friends.
Hypothesis 3	Higher levels of political sophistication are related to higher levels of awareness about the political alignment of one's Twitter friends.

The survey-question targeting the respondent's perception of their Twitter network slant required the respondents to distribute their Twitter friends into three political groups: liberals, moderates, and conservatives[6]. We provide a visualization of such an answer format in the online appendix (Figure S2).

[4]`www.yougov.com`, *Last accessed: 9th December, 2019*.

[5]We elaborate in more detail about potential sources of dropout and whether our final sample is representative of the U.S. Twitter population in section S2 and S3 respectively.

[6]The exact question was: *"Think of the users you are following on Twitter. How balanced or biased do you*

The most striking insight is that respondents assumed liberal Twitter users to make up the majority of their Twitter network. On average participants expected 45.8% of their Twitter network to be liberals while the expected share of conservative Twitter friends was 25.4% and moderates were expected to make up 28.9% of the respondents' networks.

Despite us not randomizing the ordering of the categories of the question, using a similar question[7] we find that liberal respondents expect significantly more Twitter friends to have the same opinion than conservative respondents (75.7% vs. 66.0%, t-test p-value < 0.001) – thus other independent questions also indicate perceptions of larger liberal shares. We also show in the online appendix (section S4) that these perceptions of a liberal majority among Twitter networks are not an artifact of inattentive responding and therefore conclude that there is a significantly higher share of liberal Twitter friends expected by the respondents. Additionally, we find that a non-negligible number of respondents (n=35; 14.1%) assumes a completely neutral Twitter network slant. These are users that either assumed that 100% of their Twitter friends fall into the moderate category (n=7) or chose values for the liberal and conservative group that effectively balanced out.

Measurement of the Twitter network

The objective is to measure the respondent's Twitter network characteristics such that we can extract information equivalent to the dimensions elicited in our survey. This required retrieving every Twitter friend of each respondent via the Twitter API[8] and subsequently estimating a political alignment score with the procedure of Barberá et al. (2015) for each respondent-friend-pair ($n_{friends}$=246.693; see also Figure S1 for a visualization of the data collection procedure in the online appendix). The method uses correspondence analysis (Greenacre 1993) to match the Twitter friends of a Twitter user against a list

personally think your newsfeed is? In your opinion, the percentage of people you follow on Twitter are: [Liberals, Moderates, Conservatives]" and the sum of the responses of the three sliders was required to add up to 100%.

[7]The exact question was: *"Earlier you told us that you are on Twitter. What proportion of the accounts you follow hold political opinions similar to yours (e.g., if you lean left, how many lean left, too)?"* and respondents provided estimates between 0 and 100 representing the share of accounts presumably having the same opinion as themselves.

[8]`https://developer.twitter.com/`, *Last accessed: 9th December, 2019.*

of known political elites to produce a numeric estimate indicating the political alignment of a Twitter user. The method is designed specifically for the U.S.-Twitter context which suits our research question. It has received a tremendous amount of attention in the political science community (e.g., Eady et al. 2019) and is arguably the most established strategy to estimate a Twitter user's political alignment. As the numeric uni-dimensional alignment-indicator is "standardized to have a normal distribution with a mean of 0 and a standard deviation of 1 [...]" (Barberá et al. 2015, p. 1533), we can distribute the Twitter friends of a respondent into three groups that should match approximately the survey question's categories. Following this idea, we were able to split the distribution into terciles by assuming a respondent's Twitter friend to be liberal if their estimate $f_{alignment}$ falls into the range of $f_{alignment}$ $\in$ [$-\infty$,-0.435), moderate if $f_{alignment}$ $\in$ [-0.435, 0.435] and conservative if $f_{alignment}$ $\in$ (0.435,∞]. Considering only Twitter friends that we were able to classify (avg. = 77.1%), we find that the average share of liberal friends was 34.6%, the share of conservative friends 47.9% and moderates made up 17.4% on average. This is our first striking observation: while perceptions were on average leaning towards a liberal slant, we find a disproportionately high share of conservative friends among the Twitter networks of our respondents. 37.5% of our respondents had a Twitter network where the liberal friends made up the majority, while 56.6% had more conservative friends than any other group. We observed 4.3% of cases where we had ties, but only in 1.6% of cases where moderates were the most dominant group.

Biased perceptions

The measures introduced thus far allow us to systematically investigate which factors determine respondents' perceptions and establish whether they are indeed affected by biases as hypothesized. We assumed that respondents expect a disproportionate amount of users in their network to have the same opinion as themselves. In Table 2, we present the results of weighted censored Tobit regression models on the discrepancy between perceived and observed share of liberal (Model 1), conservative (Model 2), and moderate (Model 3) Twitter friends where we estimate the impact of the self-reported political alignment.[9] We hypothesize that respondents will expect a disproportionately high amount of Twitter friends with the same opinion among their Twitter network (H1). We control for the respondent's gender, age, income, education, respondent's racial identity, and level of political sophistication.

As reported in Table 2, we find a significant impact of self-reported political alignment on the perceived share of the Twitter friend group with the same political alignment. This confirms our FCE-hypothesis (H1) that people expect significantly more persons in their Twitter network to have the same opinion as they do: Liberal (moderate, conservative) users expect significantly more Twitter friends to be liberal (moderate, conservative). As compared to moderate respondents, the liberal respondents have a higher likelihood that their perceptions exceed the observed share of liberal friends (the perceived share of liberal friends is on average 9.759% higher than the observed share). This effect is even more pronounced for conservative respondents with regards to their conservative Twitter friends: Here perceptions exceed observations on average by 14.337% as compared to moderate respondents. Finally, moderate respondents are more likely to provide a higher share of moderate friends than liberal or conservative respondents (Model 3). Noteworthy, liberal (conservative) respondents do not differ from moderate respondents when estimating the share of opposing Twitter friends (e.g. conservative respondents do not over- or underreport their liberal Twitter friends significantly more often than moderate respondents).

Comparison to reality

Do people have the right intuition about their Twitter network and do active Twitter users and politically sophisticated respondents have a better intuition than other respondents? In order to answer these questions, we need to compare the observed political alignment of Twitter friends to the self-reported distribution of Twitter friends provided in the survey. Specifically, we check whether the respondent's *perceived* most frequent political Twitter friend group matches the most frequently *observed* group.

[9]The dependent variable was calculated by subtracting the observed share of liberal (conservative, moderate) Twitter friends from the perceived share of liberal (conservative, moderate) Twitter friends. The dependent variable is represented by percentage points, follows a sigmoidal distribution and is naturally bounded to be between -100 and +100, thus, leading to the usage of a censored Tobit model.

TABLE 2. Ordered Logistic Regression Results: Discrepancy between perceived and observed share of political Twitter friends (by political alignment).

	Dependent variable: Discrepancy between perceived and observed share of political Twitter friends.		
	Liberal Tw. fr.	Conserv. Tw. fr.	Moderate Tw. fr.
Political alignment: conservative	1.902	14.337***	-16.24***
	(4.958)	(4.63)	(4.033)
Political alignment: liberal	9.759**	6.389	-16.148***
	(4.353)	(4.065)	(3.54)
Controls	+	+	+
(Intercept):1	-0.299	-17.066**	17.365**
	(8.66)	(8.087)	(7.043)
(Intercept):2	3.194***	3.125***	2.987***
	(0.049)	(0.049)	(0.049)
N	216	216	216
Log Likelihood	-965.82	-951.49	-922.56
AIC	1959.64	1930.97	1873.12

*p < .1; **p < .05; ***p < .01

If a respondent correctly anticipated the most prominent Twitter friend group in their network, this suggests the respondent has an accurate "awareness" of their Twitter network slant. Overall, 51.4% of the respondents were able to correctly anticipate this group. This is a rather positive finding – although not overwhelmingly encouraging – as the baseline accuracy of a random guess would be 33%.

As a robustness check, we also included two alternative measurements of a respondent's awareness which involve (a) the direct application of the procedure of Barberá (2015) to the respondents' Twitter network or (b) a more fine-grained numeric estimate that represents the average discrepancy between the anticipated and the observed share for each Twitter friend group (liberals, moderates, conservatives). The first alternative measure was constructed by applying the procedure of Barberá et al. (2015) (see section S8) directly to the respondent's Twitter network and then comparing the resulting indicator – negative values resembling a liberal Twitter network and positive values representing a conservative Twitter network – to the tendencies of the respondent's perceptions ($Perception_{conservative} - Perception_{liberal}$). This indicator allows then for a control of our main findings as we have a more direct application to respondent information in a more comparable approach to other research. In a second alternative approach, we compare the perceived share of each political Twitter friend group with its observed share, average over all three groups for each respondent resulting in a numeric indicator representing the average discrepancy between the perceived and observed distribution (see section S8 in the online appendix for a more detailed discussion). We included this third measurement of awareness in order to evaluate the accuracy of the respondent's anticipation as it enables the evaluation of correctness in the form of an average numeric discrepancy. However, we caution in advance of an over-interpretation of this indicator as it might not be feasible for respondents to correctly anticipate the correct share of each political group among their Twitter network. As described above, we subsequently test whether Twitter activity or political sophistication helps identify the correct Twitter network slant and report on the results of a set of weighted logistic regression models in Table 3. We again control for gender, age, income, education, ethnicity, and self-reported political alignment.

No convincing evidence for consciousness gained passively through Twitter activity In line with Levordashka and Utz (2016), we first analyzed our hypothesized relationship of awareness via information availability through more Twitter activity (H2). As we do not have observational log-data with regards to the respondent's time spent online we approach this relationship via several indicators that we associate with Twitter activity. These include (a) the number of published tweets, (b) whether a respondent published any tweets, (c) self-reported activity levels,[10] (d) the recency of Twitter use measured via days since the last published Tweet,[11] (e) whether the respondent published a Tweet in the last month (last 4 months, last 6 months) leading up to the data collection period, (f) the approximate number of changes the respondent made to their Twitter network during the six months leading up to the questionnaire, and (g) whether a respondent recently started or stopped following a political elite of the U.S. (see the online appendix in section S5 and Barberá 2015).

Overall, we find only negligible support for our hypothesis that passive knowledge collection through Twitter activity leads to better awareness of one's Twitter network slant. While most indicators

[10]The exact question was "Previously, you told us that you have a Twitter account. Today we want to learn more about your Twitter use. How frequently do you check Twitter?" and respondents could choose from eight categories: (a) several times a day, (b) about once a day, (c) 3 to 6 days a week, (d) 1 to 2 days a week, (e) every few weeks, (f) less often, (g) never, (h) don't know.

[11]Date of reference is April 1st, 2019.

related to Twitter activity were not indicative of the respondents' awareness of their Twitter network slant (Table 3), whether or not they published at least one Tweet throughout the account's lifetime was associated with a higher probability to better anticipate the most frequent political group in their network (0.553 vs. 0.326 for people who did not publish any Tweet, Fisher exact test p-value < 0.01). Basic levels of involvement may be a requirement for a basic understanding of one's Twitter environment, but this effect is not significant to conventional standards when controlling for other variables. When fitting our model to (a) the ability to predict the average Twitter network slant measured via the estimate of Barberá et al. (2015) or (b) the average discrepancy between perceived and observed share of Twitter following-groups, we also do not find any meaningful impact of the activity on awareness (see section S8 in the online appendix for a more detailed explanation). We conclude that our results are not in line with the findings of Levordashka and Utz (2016): Twitter activity may help understand the characteristics of one's surroundings but neither self-reported nor observed levels of Twitter activity were indicative of a better intuition of the average political slant of one's Twitter network.

TABLE 3. Logistic Regression results: Ability to predict most frequent Twitter friend group

	Dependent Variable: Ability to predict most frequent Twitter friend group		
	(1)	(2)	(3)
Recently published tweets? (last 3 months, dichotomous)	−0.009		−0.136
	(0.382)		(0.409)
Self-reported activity (ordinal)	0.096		−0.067
	(0.100)		(0.111)
# changes to Twitter-netw. (numeric)	−0.001		-0.001^{**}
	(0.0004)		(0.0005)
Politically sophisticated (dichotomous)		1.090^{***}	1.287^{***}
		(0.388)	(0.391)
Politically interested (ordinal)		0.693^{***}	0.772^{***}
		(0.186)	(0.205)
Controls	+	+	+
Constant	−0.702	−1.165	−0.724
	(1.155)	(0.927)	(1.155)
N	229	229	229
Log Likelihood	−126.065	−109.391	−105.889
AIC	282.130	246.781	245.778

*p < .1; **p < .05; ***p < .01

Active involvement leads to more accurate assessments Finally, we argued that Twitter users who have higher levels of political sophistication will more likely correctly anticipate the average Twitter network slant, i.e., the most frequent political Twitter friend group (H3). There is a long-standing discussion on how to best measure political sophistication (see e.g. Luskin 1987; Hutchings and Piston 2011; Gilens 2001) and the presumably low levels of political sophistication of U.S. residents has been extensively studied (e.g., Converse 1964). We measured political sophistication in line with XXX Pablo: Can you add an appropriate reference here and explain briefly why the questions with regards to political knowledge were used as they were? via closed questions that probed a respondent's knowledge about ongoing political affairs and events in four waves with different questions.[12] Overall, we classified persons who answered all questions in any of the four waves correctly as persons with high political sophistication. After also filtering for respondents for whom we were able to calculate a Twitter network slant indicator we find that 61.0% of our respondents answered in any of the four waves every question correctly. The results suggest that politically sophisticated respondents were on average right about their most frequent political Twitter friend group among their Twitter network in 59.2% of cases correctly while politically less sophisticated respondents were only right in 39.2% of cases (Fisher's exact test p-value < 0.001). Additionally, if Twitter network slant is conceptualized with the procedure by Barberá et al. (2015), politically sophisticated respondents were able to correctly predict the direction of the resulting slant indicator in 82.1% of cases while politically less sophisticated participants were on average right about the direction in only 54.7% of cases (Fisher's exact test p-value < 0.001). Participants who were more knowledgeable about ongoing political affairs thus were more likely to identify the most prevalent political group of Twitter friends in their network and correctly anticipate the average political alignment of their Twitter network.

When controlling for other confounders (Table 3), we still find support for an impact of political sophistication on the ability to correctly predict the most frequent Twitter friend group. Additionally, the numeric conceptualization of political sophistication, as well as self-reported political interest (categorical and dichotomized), are positively related to the ability to correctly predict one's Twitter network. Furthermore, when we fit our models to alternative dependent variables – (a) ability to

[12] See online appendix section S6 for the full set of questions.

anticipate the correct Twitter network slant and (b) the average discrepancy between perceived and observed share of each Twitter friend group – we also find a positive relationship between political interest and awareness. Political sophistication helps anticipate the correct Twitter network slant (case a) but does not impact the accuracy of the estimate of one's Twitter network slant (case b; see section S8 in the online appendix).

This finding might also be related to other determinants and it is important to consider them here. One alternative explanation might expect people who are more politically sophisticated to know more about political facts because they follow more news related accounts or political elites (Anspach et al. 2019; Park and Kaye 2019; Beam et al. 2016; Dimitrova et al. 2014; Chaffee and Kanihan 1997). A higher share of these accounts in the network could have the advantage for respondents to more straightforwardly detect the overall tendency of their Twitter network. If this explanation is true, politically sophisticated respondents should, therefore, follow a higher share of political elites, may have a stronger Twitter network slant and thus have an easier time identifying the basic tendency. In our sample, politically sophisticated participants follow on average 30.9 political elites (median: 12),[13] while respondents with lower sophistication scores only follow about 21.8 elites (median: 6), but this difference is marginal (Welch Two Sample t-test p-value = 0.08; Kruskal-Wallis rank sum test p-value: 0.06). If we fit a simple logistic regression on the ability to correctly predict one's Twitter network slant, include political sophistication as an independent variable and control for the number of followed political elites, the effect of sophistication is still significant ($p < 0.01$). Additionally, we do not find meaningful differences in the average observed Twitter network slant between sophistication levels using two alternative conceptualizations of Twitter network slant (see section S8 in the online appendix for a more detailed descriptions of these indicators). Taking these findings into account, we are convinced that higher levels of awareness among politically sophisticated Twitter users are not due to more news sites or political accounts being subscribed to.

We hypothesized that political sophistication enables respondents to better evaluate the characteristics of their Twitter network. The findings of others suggest that political sophistication relates to better performances when trying to detect politically aligned communication patterns (Sniderman

[13] See online appendix in section S5 for a list of recognized political elites.

et al. 1991). In our analysis, we can confirm that respondents with higher levels of sophistication were more likely to predict the most frequent political Twitter friend group in their network. This effect is visible for self-reported measures political interest as well as more reliable measures of factual political knowledge. Additionally, we showed that this relationship cannot be explained by methodological problems or inattentiveness of the respondent (see online appendix in section S4). Also, politically sophisticated respondents in our survey reportedly receive more often political news from TV (t-test p-value < 0.05), print media (t-test p-value < 0.05) and the Internet (t-test p-value < 0.01) than other respondents in our sample. As hypothesized we thus attribute the increased levels of awareness of politically sophisticated Twitter users to the respondent's active involvement with U.S. political affairs and the resulting better ability to correctly apply heuristics (Sniderman et al. 1991) and draw more accurate conclusions.

DISCUSSION

Echo chambers have been considered a major threat to democracy and the media has caught up by informing the public about the dilemma. However, given that people may be aware of the problem at hand *and* are willing to improve their consumption behavior, would they be able to make the correct adjustments to their online environment – e.g. diversify their information diet? To answer this question, we analyze the perceptions of users of the microblogging and social media service Twitter about the political slant of their network. Generally speaking, we find that Twitter users in our sample expected on average liberally slanted Twitter networks – despite our observations indicating a more conservative information diet. More importantly, we find that the *False Consensus Effect* (FCE) – i.e. people assume a disproportionally large amount of a population to have the same characteristics as they do (Fabrigar and Krosnick 1995) – to play a major role when it comes to the perceptions about one's Twitter network. In our survey, liberal (conservative, moderate) respondents assumed that their Twitter friend network consists of a high amount of liberal (conservative, moderate) Twitter friends – independently of the actual distribution of Twitter friends. This finding of the FCE is remarkable as Barnidge (2017) finds that social media users generally expect more political disagreement than non-users and they perceive more political disagreement on social media platforms than in other settings. The communication environment, i.e. the differences in the number of tweets published by the various political Twitter friend groups, were not impacting these perceptions.

Twitter users are in general aware of their communication environment. Overall, 51.4% of our respondents were able to correctly predict the most frequent political Twitter friend group in their Twitter network while 71.3% were able to anticipate the general direction of their Twitter network slant. As an understanding of one's situation is a basic requirement to adapt one's consumption behavior these insights provide some hopeful perspective with regards to the echo chamber dilemma. Based on the concept of ambient awareness (Leonardi 2015) and the findings of Levordashka and Utz (2016) we hypothesized that higher levels of Twitter activity are beneficial for the ability to correctly predict one's Twitter network slant. However, contrary to our expectations Twitter activity – self-reported or measured – was not indicative of such heightened awareness. On the other hand, political sophistication and interest proved to be clear determinants of the ability to correctly anticipate one's Twitter network slant. Familiarity with ongoing political affairs and events is achieved through active involvement with what is happening. This familiarity then helps consciously navigate the online sphere and more accurately determine the position of one's surroundings.

LIMITATIONS AND FURTHER RESEARCH

This project analyzed perceptions about politically slanted information environments and therefore contributes to research on the intersection on echo chambers and policies that aim to ameliorate the problem. However, our analyses did not include any tests of the actual willingness of our respondents to make changes to their Twitter diet and we are agnostic to how one should normatively proceed from here. However, it is noteworthy that e.g. Bail et al. (2018) find that following content of the opposite political side increases polarization, cautioning against potential strategies that simply suggest diversification of news diets. More research is needed that looks specifically at the interrelationship between perceptions about news diets and the normative intentions of the consumers.

As an outline, we investigated the relationship between awareness about one's Twitter network slant and perceptions about polarization and feelings towards opposing political groups. In order to do so, we utilize questions that asked respondent's feelings in the hypothetical case if their child would marry a Trump supporter and how large they perceive the difference between Democrats and Republicans. We find that respondents who overestimate the share of liberal Twitter friends have significantly more negative feelings towards Trump supporters while respondents who overestimate their conservative Twitter friends share more positive feelings, *independently* of whether the persons consider themselves liberal or conservative (see S9 in the online appendix). These findings demonstrate underline the need for further investigations of perceptions of cross-cutting content in addition to the already existing research on factual exposure to cross-cutting content.

We would also like to note that, of course, the observational nature of our study only allows us to recognize significant trends and cannot definitely establish causal relationships. Finally, other research may extend these findings with a more comprehensive design that includes other sources of news (apart from Twitter) or extend its scope to other countries than the U.S.

This study though is the first work that is able to provided unique insights into Twitter users' perceptions of the political slant of their surroundings. It combines the classical concept of a "False Consensus Effect" (FCE) (Ross et al. 1977) with theoretical mechanisms from opinion climate research (Noelle-Neumann 1974) showing that Twitter users' political self-identification impacts their perception of their environment. Additionally, we demonstrated that active interest in ongoing political affairs is positively related to a better awareness of one's political Twitter diet. We believe it is unrealistic to expect sudden changes to political interest but changes to the "supply" side such as increased transparency through the European General Data Protection Regulation, [14] might already positively impact our ability as researchers to gain insights into political behavior on digital media more broadly.

[14] EU-GDPR, `https://eugdpr.org/`

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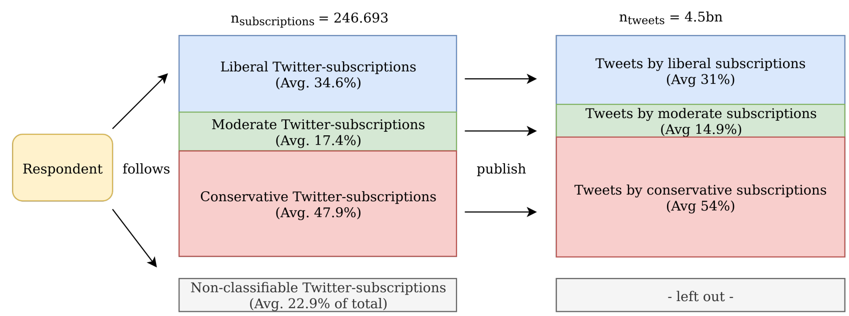
ONLINE-APPENDIX

S1. DATA COLLECTION PROCEDURE AND AVERAGES

Figure S1 visualizes the framework for our data collection. For each respondent that provided a Twitter handle, we retrieved at various dates (November, 2018; January, 2019; February, 2019; March, 2019 and April, 2019) the complete list of Twitter friends. Subsequently, we collected profile Information for all these Twitter friends i.e. their list of Twitter friends and the total number of published Tweets.

FIGURE S1. **Data collection procedure and average shares of Twitter friends and their statuses**



S2. FILTERING AND DROPOUT

When investigating our hypotheses, we require an indicator for the general awareness of the respondents' Twitter network slant. To calculate the indicator, several conditions must be met. First, respondents need to provide a valid Twitter ID which enables the linkage of self-referential survey data to observed Twitter activity data – a condition which was met by 458 of the original 1339 respondents respondents. Second, to make any statements about the Twitter network of a respondent, Twitter users are required to follow at least someone on Twitter which leaves us with n=345 observations. Third, we are required to calculate the political alignment for at least one person in this Twitter network of each participant leaving us with n=334 valid observations. Additionally, we lose respondents who did not participate in the seventh wave where the question about one's Twitter network was included, which leaves us with a sample-size of n=271.

Finally, we filter our data set in terms of Twitter friend numbers and exclude every person that followed more than 10.000 Twitter users and – more importantly – less than 10. Filtering the data set to only include respondents with 10 or more Twitter friends helps limiting the analysis to meaningful Twitter network slant estimates as people below this threshold are prone to being biased by a few influential classifications. We exclude persons who follow more than 10.000 Twitter users as we, first, consider them not to be representative of the Twitter population and, second, as a cautionary measure as we assume dishonest provisions of popular celebrity accounts. This leaves us with a final sample-size of n=245 which is the baseline for most of our analyses.

S3. REPRESENTATIVENESS OF THE SAMPLE AND THE ONES THAT PROVIDED A TWITTER USERNAME

In order to determine whether our sample is representative of the U.S. population we compare our sample to indicators provided by Pew Research (Wojicik and Hughes 2019) as this data collection also allows for comparisons between Twitter users in our sample and an estimate of the U.S. Twitter population. The information for the U.S. population comes from the Pew research's "American Trends Panel" which includes 13,569 panelists and collection waves since 2014. Information about the U.S.-Twitter population originates from a nationally representative survey conducted from Nov. 21st and Dec 17th, 2018 among a sample of 2,791 U.S. adults aged 18 or older who have a Twitter account and provided the Twitter handle to Pew Research.

S4. ATTENTION CHECK

Inattentiveness may be a common cause for some findings and we explain in the following how we utilize an attention check included in the questionnaire to rule out these possibilities. Attention checks were implemented in the form of trick questions that started out as normal questions but then took a turn in their last words and requested respondents to answer in a specific pattern to demonstrate their attention. Overall, 11.1% of respondents passed this attention check in the wave where the question concerning a respondent's Twitter network slant was included. The exact question was:

> "Many people own smartphones nowadays. How about you: Do you own one, and if yes,

TABLE S4. Comparison of sample to U.S. population and Twitter-users to Twitter population

	U.S. population	YouGov-sample	U.S.-Twitter-population	YouGov-Twitter-users
Age				
18–29	21 %	5 %	29 %	6 %
30–49	33 %	24 %	44 %	26 %
50–64	26 %	33 %	19 %	37 %
>65	20 %	38 %	8 %	31 %
Education				
Less than high school	10 %	1 %	4 %	1 %
High school graduate	59 %	16 %	54 %	15 %
College graduate+	31 %	82 %	42 %	84 %
Income				
<$30.000	30 %	22 %	23 %	24 %
$30-$75,000	33 %	49 %	36 %	47 %
$75,000	32 %	29 %	41 %	29 %
Gender				
Female	52 %	53 %	50 %	53 %
Male	48 %	47 %	50 %	47 %
Race				
Black	11 %	8 %	11 %	9 %
White	64 %	83 %	60 %	80 %
Hispanic	15 %	4 %	17 %	5 %
Political leaning				
Leaning: Democrats	52 %	55 %	60 %	63 %
Leaning: Republicans	43 %	40 %	35 %	33 %
N	13,569	1,339	2,791	458
Note	*Information about the U.S. population and U.S. Twitter-population were retrieved from Pew Research (Wojicik and Hughes 2019)*			

what type of smartphone? Specifically, we want to know whether you actually take your time to read the questions and follow our instructions. To demonstrate that you read this far, skip this question and just type „read“ in the text field below.”

First, we utilize the attention check to evaluate the impact of a lack of effort on the potential inflation degree of liberal Twitter friends. If respondents provided inflated anticipation values of liberal Twitter friends because they were actually answering the question without spending enough time on it, we should assume that this inflation is higher for participants who provably did not put as much effort into answering as others. However, we do not find meaningful differences in the expected share of liberal Twitter friends between respondents who passed and respondents who did not pass the attention check (46.7% vs. 44.7%, Welch Two Sample t-test p-value = 0.588). Challenging this robustness-check would be the argument that *every* respondent answered this question incorrectly, however, we argue that the general finding that there is a relatively strong correlation between expected and observed share (liberal: 0.525, moderate: 0.110, conservative: 0.617) proves that overall respondents answered this question correctly.

Second, one could argue that our finding of an FCE may be attributed to inattentive responding. Following this logic, respondents select their opinion (e.g. liberal) and later in the questionnaire – when being requested to provide an estimate of their Twitter network's political alignment – also mindlessly provide high estimates of a category they identify with (e.g. liberal Twitter friends). We rule out the possibility that persons answer to this question intuitively by also controlling for inattentive responding in additional regression models, where the effect of self-reported political alignment is still significant (see Table S5).

TABLE S5. Ordered Logistic Regression Results: Discrepancy between perceived and observed share of political Twitter friends (by political alignment) with attention check included.

	Dependent variable: Discrepancy between perceived and observed share of political Twitter friends.		
	Liberal Tw. fr.	Conserv. Tw. fr.	Moderate Tw. fr.
Political alignment: conservative	2.651	12.974***	-15.625***
	(4.99)	(4.622)	(4.058)
Political alignment: liberal	9.888**	6.154	-16.042***
	(4.341)	(4.021)	(3.531)
Attentive (W7)	-3.944	7.181**	-3.237
	(3.568)	(3.305)	(2.902)
Controls	+	+	+
(Intercept):1	3.114	-23.28***	20.166***
	(9.17)	(8.493)	(7.458)
(Intercept):2	3.191***	3.114***	2.984***
	(0.049)	(0.049)	(0.049)
N	216	216	216
Log Likelihood	-965.21	-949.15	-921.94
AIC	1960.42	1928.31	1873.88

*p < .1; **p < .05; ***p < .01

Third, inattentiveness could be an alternative explanation for both lower scores of political sophistication and lower levels of awareness of one's Twitter network slant as the nature of the political-sophistication-questions did not only probe the respondent's knowledge about politics but also passively their attention to the survey. Participants who were only skimming through the survey were presumably more likely to answer a question incorrectly and probably were also less willing to spend enough time to think about their Twitter network. In this sense, inattention would influence both political sophistication measurement and the accuracy of one's slant anticipation. We can test whether respondents who passed the attention check differ from inattentive respondents concerning their political sophistication levels and their anticipation accuracy. If inattentiveness influenced negatively both sophistication levels and anticipation through a general lack of interest, we would expect differences between attentive and inattentive respondents with regards to those two variables. However, we do not find meaningful differences between attention levels with regards to both indicators. Additionally, a logistic regression model on the ability to predict one's Twitter network slant which included political sophistication as an independent variable and controlled for attention proved the robustness of the effect of sophistication.

S5. LIST OF ELITES

Resulting from the correspondence analysis (Greenacre 1993) is a list of political elites that have been used to determine the political slant of Twitter users (Barberá 2015; Barberá et al. 2015; Eady et al. 2019). In our analyses we used an updated list which can be retrieved from `https://github.com/pablobarbera/twitter_ideology/blob/master/2018-update/phi-ideal-points-201807.csv` (*Last accessed: 9th December, 2019*.). We refrain from attaching a full list in this appendix due to space reasons.

S6. POLITICAL SOPHISTICATION

Political sophistication was probed in wave 2, wave 4, wave 5 and wave 6. Respondents were required to determine the truthfulness of several statements. We attested political sophistication (as used in our regression models) if a respondent provided the correct answers to every statement in any of the four waves. In all four waves the question was introduced like this:

TABLE S6. Logistic Regression results: Ability to predict most frequent Twitter-subscription-group with attention check included

	Dependent Variable: Ability to predict most frequent Twitter-subscription group		
	(1)	(2)	(3)
Recently published tweets? (last 3 months, dichotomous)	0.191		0.170
	(0.324)		(0.341)
Self-reported activity (ordinal)	0.127		0.062
	(0.082)		(0.088)
# changes to Twitter-netw. (numeric)	−0.0003		−0.001
	(0.0005)		(0.0005)
Politically sophisticated (dichotomous)		1.129^{***}	1.172^{***}
		(0.350)	(0.359)
Politically interested (ordinal)		0.339^{**}	0.324^{**}
		(0.150)	(0.154)
Passed attention check (dichotomous)	0.400	0.379	0.387
	(0.301)	(0.312)	(0.314)
Constant	-1.898^{*}	-1.494^{*}	-1.966^{*}
	(0.991)	(0.898)	(1.044)
N	229	229	229
Log Likelihood	−143.102	−134.490	−133.419
AIC	318.204	298.980	302.837

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

"In the following you see some events that have or have not taken place in the past couple of weeks. Please choose the events that you believe have indeed happened."

and for wave 2 (April, 2018 – November, 2018) events were (True answer in parentheses):

1. Donald Trump and Kim Jong Un met in Singapore (True)
2. The U.S. government decided to permanently drop out of the G7 meetings (False)
3. Thousands of immigrant families were separated at the border with Mexico after a change in border control policies (True)
4. Kim Kardashian met with President Trump in the Oval Office (True)
5. The economy grew at a 0.5% rate in the third quarter of 2018 (False)
6. Justice Ruth Bader Ginsburg announced she was stepping down from the Supreme Court (False)
7. The trial against former Trump campaign chairman Paul Manafort began (True)
8. The Spanish national soccer team won the World Cup (False)

and for wave 4 (April, 2018 – November, 2018) events were (True answer in parentheses):

1. A caravan of Central American migrants crossed into Mexico with the eventual goal of reaching the United States. (True)
2. A Russian national was charged with attempting to interfere in the 2018 U.S. midterm elections. (True)
3. Former Microsoft chairman Bill Gates died of cancer. (False)
4. Macy's declared bankruptcy. (False)
5. Donald Trump paid a million dollars to Elizabeth Warren after she proved her Native American ancestry with a DNA test. (False)
6. Kanye West met in the Oval Office with President Donald Trump. (True)

For wave 5 **and** 6 (December, 2018 – February, 2019) the events were (True answer in parentheses):

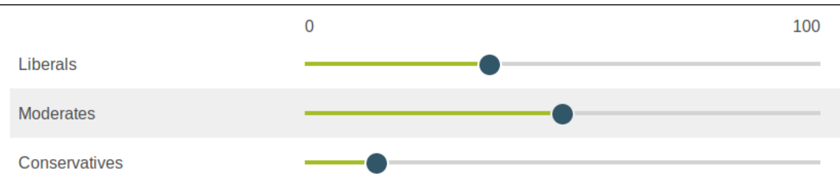
1. A wildfire in California killed more than 80 people. (True)
2. President Trump's former lawyer pleaded guilty to lying to Congress. (True)

3. Michelle Obama and Melania Trump appeared together on Oprah. (False)
4. Mark Zuckerberg stepped down from his role as Facebook's CEO. (False)
5. Theresa May (UK's prime minister) reached an agreement with European Union authorities about UK's decision to leave the European Union. (True)
6. U.S. border agents used tear gas against migrants who were trying to cross the border from Mexico (True)

S7. LINKED SLIDER QUESTION

Figure S2 visualizes the question where the respondent's perception about their Twitter network was probed.

FIGURE S2. Linked slider question: Perceptions on Twitter network (W7)



S8. ALTERNATIVE AWARENESS CONCEPTUALIZATIONS

We additionally, test our findings of determinants of accuracy of predictions (Twitter activity and political sophistication) with alternative measures of a respondent's ability to predict their Twitter network slant. While the above tests (section 3.4) were limited to the respondent's ability to predict the most frequent political group of Twitter friends we retested our models with (a) another dichotomous conceptualization of Twitter network slant using the procedure of Barberá (2015) and (b) a more fine-grained numeric classification of awareness using the average discrepancy between the perceived and observed shares of Twitter friend groups.

Conceptualization with tweetscores estimate (dichotomous)

Here, we first retrieved numeric estimates – each representing the political alignment of a respondent's Twitter network – by applying the procedure described in section **??** on the Twitter friends of each respondent. The results range from -2.32 (extremely liberal) to +2.58 (extremely conservative). Second, we evaluated the respondents' perceptions only in terms of the perceived share of liberal and conservative Twitter friends and checked whether a respondent assumed on average a liberal or conservative slant ($Perception_{conservative} - Perception_{liberal}$). Next, we tested if the perceived slant direction matched the observed slant direction (with a small tolerance interval of 0.1) and attested "awareness" in case of a match. Additionally, we attested respondent's who perceived their Twitter network to not be biased at all ($Perception_{conservative} - Perception_{liberal}$=0) awareness if the procedure of Barberá (2015) resulted in an estimate close to zero (-0.1, 0.1). The resulting alternative "awareness" indicator has a relatively high correlation (0.55) with the previously used dependent variable. Our models (see Table S7) show only marginally different results: the effect of basic levels of engagement on Twitter in the form of whether a respondent published any Tweet throughout their Twitter lifetime on the ability to predict the Twitter network slant is now more pronounced. Additionally, the fact whether a respondent recently added or removed a political U.S. elite relates to a better intuition about one's Twitter network slant. Concerning political sophistication, we still find evidence for statistically significant better ability of politically interested and sophisticated respondents to correctly predict the average Twitter network slant. However, while the effect of political sophistication (numeric conceptualization) still points in the anticipated direction, we cannot confirm any meaningful effect of this variable in this setting.

Conceptualization with numeric estimate of awareness

Second, we investigate our findings of determinants of accuracy of predictions (Twitter activity and political sophistication) with a more fine grained numeric conceptualization of awareness. A rather straightforward approach of evaluating perceptions may compare the *perceived* share of a political Twitter friend group with its *observed* share. We can do this for each group (liberal, moderate, conservative) and then average the discrepancy for each respondent. As an example, imagine a respondent who assumed to follow 50% liberal, 30% moderate and 20% conservative Twitter users (perception) but whos Twitter network actually consists of 30% liberal, 40% moderate and 30% conservative Twitter users (observation). Consequently, we may average the emerging discrepancies (liberal: |50%-30%| = 20%; moderate: |30%-40%| = 10%; conservative: |20%-30%| = 10%) which would result in an average discrepancy of 13.3%. The resulting number reflects the inverse accuracy of respondents' perceptions about their Twitter network's political alignment. We invert these numbers to retrieve an indicator that gets higher the closer a respondent's perceptions was to the observed outcome, standardize it to have a standard-deviation of 1, and subsequently use this number as an alternative dependent variable in our models (see Table S8). This indicator has a correlation of 0.46 with the previously used indicator (ability to predict the most frequent Twitter friends-group). Similar to the main results, we do not find any meaningful impact of any variable related to Twitter activity. However, we also do not find meaningful effects for indicators related to political sophistication. Only self-reported interest was predictive of a low average discrepancy. Overall, these models display a very low amount of explained variance as indicated by the R^2 and adjusted R^2.

Summarizing, robustness-checks in the form of alternative "awareness"-indicators qualify our results slightly: Twitter activity in the form of rudimentary engagement with Twitter seems predictive of the ability to recognize one's Twitter network slant, while political sophistication – and especially political interest – seem to be beneficial to both recognizing the Twitter network slant and making more accurate predictions about one's Twitter network's political alignment.

S9. IMPLICATIONS OF AWARENESS FOR POLARIZING FEELINGS

TABLE S7. Logistic Regression results: Ability to predict direction of own Twitter-network-slant

	Dependent Variable: Ability to predict direction of own Twitter-network-slant		
	(1)	(2)	(3)
Recently published tweets? (last 3 months, dichotomous)	0.214		0.104
	(0.373)		(0.396)
Self-reported activity (ordinal)	0.064		0.003
	(0.096)		(0.102)
# changes to Twitter-netw. (numeric)	0.002		0.001
	(0.002)		(0.002)
Politically sophisticated (dichotomous)		1.206***	1.145***
		(0.383)	(0.389)
Politically interested (ordinal)		0.426**	0.394**
		(0.165)	(0.169)
Controls	+	+	+
Constant	−1.724	−1.201	−1.412
	(1.122)	(1.010)	(1.172)
N	202	202	202
Log Likelihood	−108.037	−100.537	−99.826
AIC	246.075	229.073	233.652

*p < .1; **p < .05; ***p < .01

TABLE S8. Linear Regression results: Inverted average discrepancy between perceived and observed share of Twitter-subscriptions

	Dependent Variable: Inverted average discrepancy between perceived and observed share of Twitter-subscriptions		
	(1)	(2)	(3)
Recently published tweets? (last 3 months, dichotomous)	−0.019 (0.137)		−0.035 (0.136)
Self-reported activity (ordinal)	0.019 (0.035)		0.004 (0.035)
# changes to Twitter-netw. (numeric)	0.0003 (0.0003)		0.0003 (0.0003)
Politically sophisticated (dichotomous)		0.042 (0.138)	0.020 (0.141)
Politically interested (ordinal)		0.130** (0.059)	0.126** (0.060)
Controls	+	+	+
Constant	3.245*** (0.397)	3.228*** (0.342)	3.201*** (0.397)
N	225	225	225
R^2	0.065	0.081	0.086
Adjusted R^2	0.003	0.025	0.016
Residual Std. Error	0.909 (df = 210)	0.899 (df = 211)	0.903 (df = 208)
F Statistic	1.050 (df = 14; 210)	1.438 (df = 13; 211)	1.221 (df = 16; 208)

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$