The false consensus effect explains why citizens overestimate the prevalence of online echo chambers.

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Abstract

A frequently discussed phenomenon concerning online media consumption are so-called echo chambers: are social media users increasingly exposed only to information that reinforces their political views? While much research has been devoted to the prevalence of echo chambers and the potential effects of counter-attitudinal exposure, there is a research gap when it comes to the perceptions of the users themselves. How do citizens view their online information environments and are they aware of how politically slanted those environments are? By evaluating data from a representative survey of U.S. online adults linked to their Twitter data, here we offer evidence of a "false consensus" effect: citizens overestimate the proportion of people in their Twitter network that share the same ideological views as their. We observe this trend for all users,

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although its magnitude is lower for those with higher levels of political knowledge. We argue that this lack of awareness of biased information flows is a key piece of evidence that resolves the puzzle of why the concept of echo chambers has received extensive attention in academic and media circles despite the fact that empirical evidence shows that social media platforms increase exposure to diverse views.

Keywords: *social media, Twitter, awareness, ideology, linked surveys*

1 Introduction

Scientists have long warned of the potential dangers that so-called *echo chambers* might pose to democracies (for a literature review, see Tucker et al., 2018). A common formulation of this concern is that online environments foster the emergence of spaces in which like-minded views can find one another and avoid being challenged. In this environment, citizens are only exposed to information that reinforces their political opinions, which leads to the amplification of extremist ideas and the disappearance of the type of common ground required to reach political compromise and avoid gridlock (Sunstein, 2009). These dynamics are generally conceived to be the result of psychological factors, such as selective exposure (e.g., Stroud, 2010) and homophily (e.g., McPherson, Smith-Lovin and Cook, 2001), which are amplified by affordances of online environments, ranging from the ubiquity of social feedback (Settle, 2018) to the algorithms used by social media platforms to rank content (Pariser, 2011).

The concern about online echo chambers is not new. Putnam et al. (2000) already contrasted offline interactions, which "force us to deal with diversity", with "the virtual world," which "may be more homogeneous;" pointing to the use of "new 'filtering' technologies that automate the screening of 'irrelevant' messages" (p.178) as factor that could accelerate this process. It is also not specific to social media platforms – research on the success of cable news (Martin and Yurukoglu, 2017, Prior, 2007) or the spread of broadband internet access (Lelkes, Sood and Iyengar, 2017, Winneg et al., 2014) has shown that in a high-choice environment, citizens will tend to flock towards congenial political information. However, the extensive scope of customization options and the vast increase in the availability of political information on social media has been prominently theorized to worsen an already existing problem (Pariser, 2011, Sunstein, 2009). The prominence of this argument in academic and media circles is such that many online news outlets have built tools to sensitize users about the implications of biased news diets and the importance of "hearing the other side" (see e.g., allsides.com).[1]

However, recent empirical studies demonstrate that the concerns about online echo chambers have been overstated. Even if most of the information that people interact with on social media sites aligns with their existing views (Barberá et al., 2015, Boutyline and Willer, 2016), citizens are regularly exposed to cross-cutting political content (Eady et al., 2019) and, in fact, exposure to diverse views is higher than through other forms of news consumption (Barnidge, 2017, Flaxman, Goel and Rao, 2016, Fletcher and Nielsen, 2018). Similarly, ranking algorithms appear to be less important than users' own choices in shaping exposure to information through social media platforms (Bakshy, Messing and Adamic, 2015, Haim, Graefe and Brosius, 2018)

How can we reconcile the frequent concerns about the prevalence of echo chambers with the evidence demonstrating that these concerns are exaggerated? Here, we offer a potential explanation: social media users have a biased perception of the political alignment of their online environment.

When talking about the problem of online echo chambers, we currently do not know whether citizens 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 stresses the need for a further evaluation of the relationship between respondents' perceptions and reality (e.g., Barnidge, 2017). We attribute this research gap to the extensive observational efforts and costly qualitative research that were previously necessary to compare perceptions to behavior (Bernard et al., 1984). In this paper, we instead develop a novel strategy that leverages survey responses linked to social media data as an alternative to accurately compare the observed and perceived ideological distributions of online social networks

Our argument builds on a key insight from past work on perceptions of social networks: the existence of a false consensus effect, i.e., the tendency to overestimate the proportion

[1] `www.allsides.com`, *Last accessed: 20 April, 2020*

of persons having similar characteristics as oneself in a population (Fabrigar and Krosnick, 1995). We hypothesize that the false consensus effect also applies to citizens' perceptions of their social media networks. We test this hypothesis using data from one of the largest social media platforms in the U.S. – Twitter – and leveraging recent developments in ideology estimation for Twitter users (Barberá et al., 2015). This is – to our knowledge – the first direct, individual-level comparison of perceived and actual political alignment of social media networks.

Our analysis reveals strong evidence of a false consensus effect: respondents of all ideological inclinations (conservatives, moderates, and liberals) tend to systematically overestimate the extent to which their Twitter network shares their political ideology. This effect is statistically significant for respondents with low and high levels of activity on Twitter and across all levels of political knowledge, although its magnitude decreases for those that are most attentive to political events. Our findings thus suggest that increased attentiveness to online information environments may help alleviate concerns about cyberbalkanization.

2 Theory

Past research on social networks has systematically revealed that self-reported network metrics do not necessarily reflect the actual characteristics of citizens' ego networks, thus, posing a serious threat to communication research (Corman, 1990). Survey participants tend to answer such questions incorrectly and are assumed to hold biased perceptions about their communication behavior. The accuracy rate in such questions is often less than 50% (Marsden, 1990). In fact, Bernard, Killworth and Sailer (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?

2.1 *The false consensus effect*

Kunda (1990) argues that an individual's motivation is key for her search through memory, which often means that people process information in a biased way in order to arrive to their desired conclusions. One such bias 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). Introduced by Wallen (1943), the FCE has found empirical support in numerous studies (for an overview see, e.g., Marks and Miller, 1987) and seems especially relevant for research on contemporary media consumption (see, e.g., Schulz, Wirth and Müller, 2018). It postulates that a person projects their own opinion onto others and, thus, will be likely to overestimate the proportion of persons in a given reference group that are similar to herself.

The false consensus effect may be a useful heuristic that simplifies reality to help individuals cope with complex social structures (Lai, 2019). However, there are plenty of reasons for why having a good sense of one's surroundings may also be beneficial, as this could lead to an information advantage over others (Cialdini and Goldstein, 2004, Janicik and Larrick, 2005) or better access to valuable resources (Domahidi, 2018, Seo and Ebrahim, 2016). 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 to successfully navigate online resources (Hargittai and Micheli, 2019). Biased information processing has been found to be one of the key mechanisms explaining why individuals are susceptible to misinformation on social media (Bago, Rand and Pennycook, 2020). The necessity of a sufficient sensitivity to one's surroundings in an online setting is also highlighted by scenarios where awareness is being limited or altered by strong biases of resources (Garrett, Weeks and Neo, 2016) or via manipulation of the communication environment such as e.g., on social media in China (King, Pan and Roberts,

2017) or Russia (Spaiser et al., 2017).

These biased estimates of a more similar social environment boost peoples' beliefs in their own views as they are more likely to consider their opinion to be part of an inflated majority. Prior research has shown that people arrive at these self-serving conclusions because they seem more plausible to them (Kunda, 1990, Taber, Lodge and Glathar, 2001). Specifically, individuals appear to be driven by two goals: accuracy goals – i.e., they are aware of an effort-accuracy trade-off and select strategies by considering both the strategies' costs and benefits – and directional goals – i.e., they have the desire to maintain their prior beliefs (Kunda, 1990, Taber, Lodge and Glathar, 2001). We consider the FCE as one such possible prior belief which individuals may uphold and hypothesize accordingly that the self-reported ideology of a respondent will impact their perceived proportion of followed Twitter users that share their ideology. More specifically, we hypothesize that:

H1: **Twitter users will overestimate the share of people with the same opinion as themselves among their Twitter network, compared to the actual proportion**

Despite the important implications of this hypothesis 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, to our knowledge, not yet been studied extensively. Lai (2019) use survey self-reports to show that social purposes of social media usage lead to perceptions of larger networks and more diverse connections. 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 (2016) find a positive relationship between a person's Twitter activity and the knowledge about characteristics of those users a given person is subscribed to. They do not, however, extend their study to the awareness of the political characteristics of the Twitter network. Wojcieszak and Price (2012) compared perceived and recorded political disagreement in online forums and found that perceptions are only weakly related to observations. 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. Guess et al. (2019) use a similar empirical approach as us – combining survey responses and social media data – to show that self-reported measures about frequency of political use of Twitter are correlated with *actual* use, although they do not explore perceptions of users' networks and their ideological composition. There is, to the best of our knowledge, no study to date that systematically evaluates a user's ability to recognize the political alignment of her online social network.

2.2 *The role of online activity and political sophistication*

For users to arrive at valid estimates of the political slant of their online social network, they, first, 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 level of the user. Social media users passively build awareness of each other through persistent sharing of – or reactions to – status updates, thus affecting both senders and receivers of messages (Hampton, 2016). The findings in Levordashka and Utz (2016) suggest, for example, that people who spend more time on Twitter are consequently more knowledgeable about their Twitter network as they are more likely receive updates from their friends. Given that general consciousness about the online social network is one condition to then identify the political slant of this network, we hypothesize that:

H2: Higher levels of activity on Twitter are correlated with users' awareness of the political slant of their online network

To provide a proper estimate of the political alignment of one's online social network, users 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, another user. But how do users evaluate their network? Users read messages posted in one's network that appear upon visiting the platform and can at the same time see the reactions of others to the content that was shared (e.g., *likes* or *retweets* on Twitter). Typically, users neither have the time nor means to research the background of each of their connections, hence instead heuristics likely play a crucial role in their assessment. The "likability heuristic" of Brady and Sniderman (1985) describes one such potential cognitive shortcut when evaluating political issues: a user 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, Brody and Tetlock, 1991). These conclusions are more likely to be correct with more political sophistication and we, therefore, hypothesize that:

H3: Users with higher levels of political sophistication are more likely to correctly identify the political slant of their online network

3 Materials and methods

3.1 Data: survey responses linked to Twitter data

We test our hypotheses levering a unique data collection about citizens' activity on the microblogging platform Twitter. We selected this social media site due to its popularity around the world, its prominence as a focal point for political conversations, and the fact that most of the academic debate on echo chambers has focused specifically on Twitter (Barberá et al., 2015). On this platform, users can follow other users in order to receive the content (tweets) they share, as well as any tweets shared by other users that they choose to share (retweets). We refer to the users that a given account follows as their *friends*. Excluding ads, users will only see content produced or retweeted by their friends. For this reason, the characteristics of a user's Twitter network of friends will affect the information they consume.

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 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 (in our sample, average = 577.1, median = 148) and it seems implausible 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 acquaintances might come to mind first while others might be overlooked (Kunda, 1990, Litt and Hargittai, 2016, Taber, Lodge and Glathar, 2001) and, thus, the imagined network may differ from the actual connections (Kilduff et al., 2008) – a hypothesis that we also test here.

In this study, we analyzed a multi-wave survey dataset from an online representative panel of U.S. adults recruited by YouGov, which we linked to social media data for the subset of respondents that had an active Twitter account and agreed to share their profile information with us via an approved authentication app.[2] The data was collected between July 2018 and February 2019. The survey dataset (N=1,551) contains questions about political attitudes and behavior, self-reported information about online activities, and demographics.[3] The Twitter dataset collected for the subset of respondents that gave consent and had active

[2]We check the robustness of our findings with a separate dataset combining survey data and Twitter responses, which we collected using the *respondi* online panel in the US and Germany (N=326). Since the survey dataset did not include all the survey questions required to test our hypotheses, we don't report our findings in the main text of this manuscript. However, as shown in Appendix S12, for the analyses that we can run with this second dataset, we are able to reproduce all our main results.

[3]See Appendix S1 for additional details on sampling and survey data collection.

accounts (N=245) included all the public tweets they posted and monthly snapshots of their friend networks.[4]

3.2 *Measuring the political alignment of Twitter networks*

The key survey question probing the respondents' *perceptions* of the political alignment of their Twitter network required participants to assign relative shares of their Twitter friends to three political groups: liberals, moderates, and conservatives. The exact question was: *"Think of the users you are following on Twitter. How balanced or biased do you 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%. We provide a visualization of such an answer format in Figure 1. For each respondent this allows us to determine (a) which political group is perceived to be the most dominant among her Twitter network and (b) towards which political alignment she perceives her Twitter network to be biased.

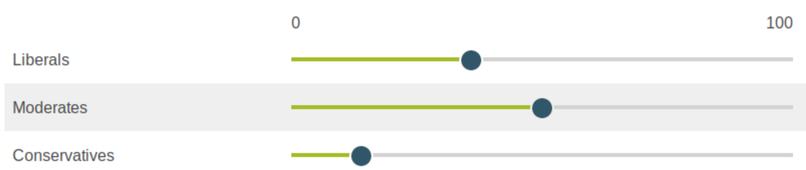

Figure 1: Linked slider question: Perceptions on Twitter network

To measure the *observed* ideological distribution of each respondent's Twitter network in a way that is equivalent to the dimensions elicited in our survey, we applied the methodology developed by Barberá et al. (2015) to estimate the political ideology of Twitter users. This approach has been extensively validated and successfully used in recent research in multiple fields (Brady et al., 2017, Eady et al., 2019, Imai et al., 2016, Rivero, 2019). The technique matches the Twitter friends of a respondent against a list of known political elites to produce a numeric estimate indicating the political alignment of a Twitter user.

To apply this method, we retrieved every Twitter friend of each respondent via the Twit-

[4]See Appendix S2 for information on the process to link survey respondents to Twitter data, and how each filter contributed to the final sample size.

ter API[5] and, subsequently, estimated a political ideology score for each of them($n_{friends}$ = 246,693; see also Figure S2 for a visualization of the data collection procedure). 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 to match the survey question's categories. Specifically, we split the distribution of users' political alingments 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 $f_{alignment} \in (0.435; \infty]$.[6]

3.3 *Dependent variables*

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? To test our three hypotheses, we need to compare the observed political alignment of Twitter friends to the self-reported distribution of Twitter friends provided in the survey. We do this using two different metrics.

First, we use the survey responses to the question shown in Figure 1 to compute **group-specific accuracy estimates**. In other words, for each respondent we can observe whether the proportion of conservatives, moderates, and liberals that they report following on Twitter is higher or lower than the *actual* proportions that we estimate by directly observing their Twitter network, and by how much.

Second, we reduce these comparisons to a single binary indicator for each user user, **respondent-specific accuracy**, which indicates whether the ideological group that the respondent perceives to be as most prevalent in their Twitter network matches the most frequently *observed* group. For example, for an individual that responds that 50% of their network is liberal, 30% is moderate, and 20% is conservative, the value of this indicator

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

[6] These cutoff values are chosen to split the population of Twitter users into three equally sized groups with regard to their political alignment.

would only be 1 if we find that Twitter users predicted to be liberal do indeed represent the plurality of the respondent's Twitter network.

We use these simple metrics to facilitate their interpretation of our findings, but in Appendix S9 we demonstrate that our results are robust when we rely on more complex measures that take into account the continuous nature of the ideology estimates for Twitter users.

3.4 *Model specification*

We test our first hypothesis concerning the false consensus effect using three different censored Tobit regression models, which evaluate how the discrepancy between perceived and observed proportions of of liberal, conservative, and moderate Twitter friends vary depending on respondents' self-reported political ideology.[7] The dependent variable (**group-specific accuracy estimate**) was calculated by subtracting the observed share of liberal (conservative, moderate) Twitter friends from the perceived share of liberal (conservative, moderate) Twitter friends. Positive values on the dependent variable thus indicate that respondents *overestimate* the extent to which that ideological group is present in their network.

Equation 1 shows the specification of the three regression model for respondent i. We use weights in our regression models to account for sampling discrepancies (see Appendix S3) and control for the respondent's gender, age, income, education, respondent's racial identity, and level of political sophistication (represented as x_j for respondent i). β_{0a} is the constant of the model, while a second intercept (β_{0b}) serves as an auxiliary statistic, and u represents

[7] We use the censored Tobit model because our dependent variable is represented as percentage points and follows a sigmoidal distribution that is naturally bounded to be between -100 and +100.

an error term:

$$perceived_{i,cons} - observed_{i,cons} = \beta_{0a} + \beta_{0b} + \beta_1 \cdot conservative_i + \beta_2 \cdot liberal_i + \beta_j \cdot x_{i,j} + u_i \tag{1}$$

$$perceived_{i,mod} - observed_{i,mod} = \beta_{0a} + \beta_{0b} + \beta_1 \cdot conservative_i + \beta_2 \cdot liberal_i + \beta_j \cdot x_{i,j} + u_i \tag{2}$$

$$perceived_{i,lib} - observed_{i,lib} = \beta_{0a} + \beta_{0b} + \beta_1 \cdot conservative_i + \beta_2 \cdot liberal_i + \beta_j \cdot x_{i,j} + u_i \tag{3}$$

The parameters of interest for H1 are β_1 and β_2. If respondents are indeed overestimating the prevalence of others with their ideological views in their social media networks, we should observe that β_1 is positive in Model 1, that β_2 is positive in Model 2, and that both β_1 and β_2 are negative in Model 3.

We test the second and third hypotheses, which examine whether users with higher levels of social media activity and political sophistication are more aware of the political alignment of Twitter networks, using binary logistic regressions. Here, since our hypotheses are at the respondent level, we use the **respondent-specific accuracy** metric, which equals to one when the respondent is able to correctly guess which ideological group is more prevalent in their network and zero otherwise. We again employ sampling weights and control for gender, age, income, education, ethnicity, and self-reported political alignment (x_j).

$$P(Y_i = 1) = \beta_0 + \beta_1 \cdot activity_{i,l} + \beta_2 \cdot sophistication_i + \beta_j \cdot x_{i,j} + u_i \tag{4}$$

As we do not have observational with regards to the respondent's time spent online we measure social media activity via a set of several related indicators from the survey and Twitter data ($activity_{i,l}$). These include (a) the number of published tweets, (b) whether a respondent published any tweets, (c) self-reported activity levels,[8] (d) the recency of Twitter

[8]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

use measured in days since the last published Tweet,[9] (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.[10] **HOW ARE THESE VALUES AGGREGATED? AND WHAT IS l IN THE EQUATION?**

We measured political sophistication via closed questions that probed a respondent's knowledge about ongoing political affairs and events in four waves with different questions.[11] Overall, we classified persons who answered all questions in any of the four waves correctly as persons with high political sophistication and included a dichotomous indicator in our models (*sophistication*). β_0 and u represent a constant and an error term, respectively.**ROBUSTNESS CHECK BASED ON AVERAGE % CORRECTLY GUESSES QUESTIONS? OR PERCENTILES?**

4 Results

Before we show the results of our regression analysis, we first report descriptive statistics for our key variables of interest. First, regarding users' *perception* of the ideological composition of their networks, we find that for most of our sample, respondents perceived that liberal Twitter users represented the plurality 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.

This finding contrasts with the *observed* political alignment of their networks, where conservatives friends actually represented the plurality of users' networks.[12] We find that

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.

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

[10]See Appendix S5 for more information about the list of political elites.

[11]See Appendix S6 for the full set of questions.

[12]In the classification of a user's network, we only consider the share of Twitter friends that we were able to classify (average = 77.1%).

the observed average proportion of liberal friends was 34.6%, the share of conservative friends 47.9% and moderates made up 17.4% on average. [13]

Figure 2 compares perceived and observed network composition for each user. Here, each point represents a survey response to the question about what proportion of a user's network is e.g. conservative (left panel, x-axis) with the actual proportion of their friends that are indeed conservative (y-axis). We find a positive correlation between the expected and the observed share of Twitter friends, which suggests that respondents do indeed have somewhat accurate perceptions of the average slant of their networks. This is primarily true for the share of liberal and conservative Twitter friends and less so for moderate Twitter friends. This figure also shows that many users overestimate the presence of aligned friends in their networks, as evidenced by the fact that many of the points are above the 45-degree line for users self-identified as conservative and liberal. **REPLACE CONTINUOUS SCALE FOR SELF-REPORTED IDEOLOGY WITH DISCRETE SCALE? AND CAN WE ADD 45-DEGREE LINE?**

Finally, regarding the respondent-specific accuracy metrics, we find that 51.4% of the respondents were able to correctly self-report the most frequent ideological group among their Twitter network. **WHAT ABOUT THE REST? In what direction were the errors? Report %**

4.1 *Evidence for the false consensus effect*

Our first hypothesis stated that respondents perceive they have a proportion of ideologically congenial Twitter friends that is larger than the actual proportion of congenial friends. In Table 1, we present the results of the weighted censored Tobit regression models (see equation 1), which we use to estimate the impact of self-reported respondent ideology on the discrepancy between perceived and observed share of liberal (Model 1), conservative (Model 2), and moderate (Model 3) Twitter friends.

[13] In Appendix S12 we replicate this analysis with the alternative sample. Although we find that these proportions are somewhat different, the key result still holds: the average ideological distribution of perceived and observed Twitter networks do indeed appear to differ strongly.

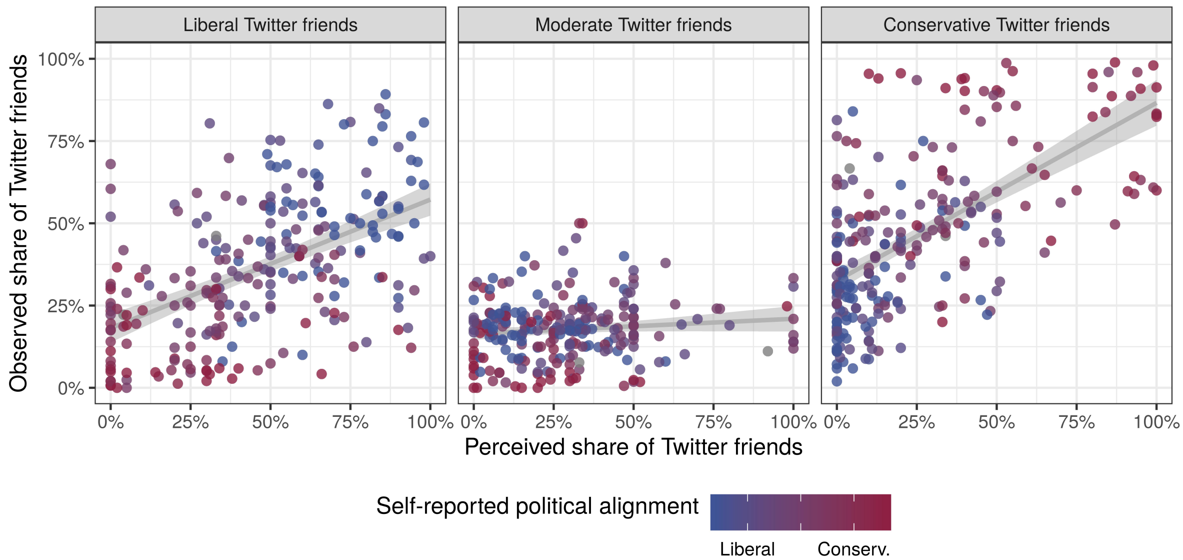

Figure 2: Perceived vs. observed share of Twitter friends by political alignment of Twitter friends and self-reported political alignment. The grey lines represent a simple linear regression model with the observed share as the dependent, the perceived share as the independent variable and an intercept. Grey lines surrounded by 95% confidence intervals; self-reported political alignment was measured on a 7-point Likert scale.

The results indicate that indeed self-reported political alignment has a significant impact on the perceived share of the Twitter friend group with the same political alignment.[14] As compared to moderate respondents, the liberal respondents in our sample have a higher likelihood for their perceptions to exceed the observed proportion of liberal friends (the perceived proportion of liberal friends is on average 9.8% higher than the observed share after controlling for the above mentioned confounding variables). This effect is even more pronounced for conservative respondents with regards to their conservative Twitter friends, for whom perceptions exceed observations by 14.3% as compared to moderate respondents. Finally, moderate respondents are more likely to provide a higher estimate for the share of moderate friends than liberal or conservative respondents (Model 3). **IS THIS THE CORRECT INTERPRETATION FOR THE COEFFICIENTS IN A TOBIT MODEL? OR ARE THE COEFFICIENTS IN THE TABLE ALREADY MARGINAL EFFECTS?**

[14]Appendix S4 shows that these biased perceptions are also not simply an artifact of inattentive user responses. We are also able to replicate the patterns here using our second U.S. and German sample (Appendix S12.4)

Table 1: Weighted censored Tobit models: 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

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$; Standard errors in parentheses.

We also find that liberal and conservative respondents do not differ from moderate respondents when estimating the share of Twitter friends with diverging political alignment, i.e., conservative respondents do not over- or underreport their liberal Twitter friends significantly more often than moderate respondents.

Given the empirical support for our first hypothesis, we conclude that users' perceptions of their online networks do vary across ideological groups, in ways that are consistent with evidence of false consensus effects. We next investigate in more detail our hypotheses regarding two potential factors that impact users' awareness of their networks' political alignments.

4.2 *Impact of activity and political sophistication on awareness*

We now turn to the question whether Twitter activity or political sophistication help users identify the ideological distribution of their Twitter networks. Model 1 in Table 2 shows that the variables we use to measure of Twitter activity are not significantly correlated with respondents' ability to identify the most frequent ideological group in their network.[15]

In other words, this first analysis shows that there is no convincing evidence for our hypothesis that passive knowledge collection through Twitter activity leads to better awareness of one's Twitter network slant (H2). We can thus conclude, contrary to the findings of Levordashka and Utz (2016), that while Twitter activity may help understand the general characteristics of one's surroundings, neither self-reported nor observed levels of Twitter activity were indicative of a better intuition of the general political alignment of one's Twitter network.

Table 2: Logistic Regression results: Ability to predict most frequent Twitter-subscription-group

	Dependent Variable: Ability to predict most frequent Twitter friend group		
	(1)	(2)	(3)
Recently published tweets?	−0.021		−0.136
(last 3 months, dichotomous)	(0.387)		(0.426)
Self-reported activity	0.077		−0.061
(ordinal)	(0.102)		(0.109)
# changes to Twitter netw.	−0.001		-0.001^{**}
(numeric)	(0.0004)		(0.0004)
Politically sophisticated		1.174^{***}	1.399^{***}
(dichotomous)		(0.410)	(0.415)
Politically interested		0.665^{***}	0.745^{***}
(ordinal)		(0.181)	(0.200)
Controls	+	+	+
Constant	−0.433	−0.989	−0.646
	(1.238)	(0.980)	(1.170)
N	220	220	220
Log Likelihood	−117.454	−101.927	−98.190
AIC	264.907	231.853	230.381

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$; Standard errors in parentheses.

We also hypothesized that Twitter users who have higher levels of political sophistication may be more likely to correctly anticipate the average slant of their network, i.e., the

[15] We find similar results when we replicate this analysis with alternative operationalizations of the dependent variable (Table S7 and S8), as shown in Appendix S9. Additionally neither self-reported nor observed Twitter activity proved to predict respondents' ability to recognize the alignment of their Twitter network on the second dataset we use (Appendix S12.5).

most frequent political Twitter friend group (H3). As described earlier, we operationalize politically sophisticated respondents as those who answered every political knowledge question correctly. These users make up 61.0% of all respondents for which we can estimate the political alignment of their Twitter networks.

Bivariate t-tests show that a larger proportion of these politically sophisticated respondents were able to correctly identify their most frequent political Twitter friend group (in 59.2% of cases) compared to the less politically sophisticated respondents (39.2% of cases; $p_{t-test} < 0.001$).[16]. This suggests that participants who were more knowledgeable about ongoing political affairs were indeed more likely to identify the most prevalent political group of Twitter friends in their network – as we expected in H3.

This finding is robust to controlling for other confounding factors in a logistic regression (Model 2 in Table 2): political sophistication is a statistically significant predictors of respondents' ability to correctly predict the most frequent Twitter friend group. Additionally, self-reported political interest (which we may consider an additional proxy for political knowledge) is also positively related to the ability to correctly predict one's Twitter network.[17]

However, it is important to note that we still find evidence of a false consensus effect among respondents with high political sophistication: the average discrepancy between perceived and observed share of each Twitter friend group (See Table S5) is similar for participants with high and low political sophistication. That is, politically more sophisticated users appear to be able to better recognize overall bias in their Twitter network but there is still a mismatch between their perceptions and the observed political alignment of their networks, consistently with H1.

There are a number of alternative explanations for the finding that political sophistica-

[16] This finding is robust to alternative operationalizations of 'correctness'. For example, if we just take the average ideology score of a respondent's friend network as ground truth, 82.1% of politically sophisticated participants were able to correctly guess whether it was liberal (lower than zero) or conservative (higher than zero), compared to 54.7% for the rest of respondents ($p_{t-test} < 0.001$)

[17] As earlier, this finding holds for predicting the tendency – no only the dominant group – of one's Twitter network (See Table S4).

tion affects Twitter users' awareness. We might, for example, expect that people who are more politically sophisticated simply know more about political facts because they follow more news accounts or political elites (e.g., Chaffee and Kanihan, 1997, Dimitrova et al., 2014). A higher share of these accounts in the network could also allow respondents to more straightforwardly detect the overall tendency of their Twitter network. If this explanation was true, politically sophisticated respondents should, therefore, follow a higher share of political elites, may have a stronger Twitter network slant and, consequently, have an easier time identifying the basic tendency.

In our sample, politically sophisticated participants follow on average 30.6 political elites (median: 12; see A[[emdox S5 for more information on recognized political elites), while respondents with lower sophistication scores only follow about 24.0 elites (median: 6), but this difference is marginal ($p_{Welch} = 0.26$; $p_{Kruskal-Wallis} = 0.07$). When fitting a simple logistic regression model on the ability to correctly predict one's Twitter network slant, including political sophistication as an independent variable and controlling for the number of followed political elites, the effect of sophistication is still significant ($p < 0.01$).

We do find, however, that politically sophisticated respondents in our survey self-reported more frequent consumption of political news from TV ($p_{t-test} < 0.05$) and the Internet (p_{t-test} < 0.01) than other respondents in our sample. This strengthens our argument that we can indeed attribute the increased levels of awareness of politically sophisticated Twitter users to the respondents' active involvement with U.S. political affairs and the resulting better ability to correctly apply heuristics and draw more accurate conclusions (see also Sniderman, Brody and Tetlock, 1991).

5 Discussion and Outlook

The question of whether social media platforms contribute to the emergence of online echo chambers is and continues to be one of the open questions in the study of political communication. While most empirical studies show that exposure to diverse views through these sites is higher than expected, there are other mechanisms that could explain why social media may still have polarizing effects. Here, we use a unique new dataset linking survey responses with social media data to offer novel evidence that may explain this asymmetry: most users overestimate the degree of bias in their online information environments.

More specifically, we found strong evidence that the *false consensus effect* (FCE) – i.e., people assume a disproportionally large amount of their Twitter friends to have the same characteristics as they do (Fabrigar and Krosnick, 1995) – plays a major role when it comes to the perceptions about one's network. In our survey, liberal (conservative, moderate) respondents assumed that their Twitter friend network consists of a high amount of ideologically congenial Twitter friends – independently of the actual distribution of Twitter friends. This finding is remarkable as Barnidge (2017) finds that citizens generally report being exposed to more political disagreement on social media. Twitter users, however, are also not completely unaware of their communication environments. 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.

One key takeaway from this results is that we as researchers should treat self-reported estimates of online networks and corresponding information diets with caution because taking them at face value bears clear risks of misreporting. This is especially important with a view towards research that relies exclusively on survey data to study behavior on social media, without trying to join it to digital trace data (Schober et al., 2016). As our approach illustrates, it is the combination of these techniques that provides unique empirical leverage. The findings in our study also align with research that has investigated systematic misreports about Twitter activity (Guess et al., 2019, Henderson et al., 2019) and contributes to a better understanding of systematic biases in survey responses.

The understanding of one's situation is a basic requirement to adapt consumption behavior and the insights we have presented 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 those expectations, Twitter activity – self-reported or measured – was not indicative of such heightened awareness. Instead, and in line with the earlier work of Sniderman, Brody and Tetlock (1991), 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 political and societal events. This familiarity then helps consciously navigate the online sphere and more accurately determine the political position of those in one's surroundings.

There are a number of recent studies that have shown that social media users are – even in the presence of echo chambers – still exposed to ideological cross-cutting content (Eady et al., 2019, Stier et al., 2020). Yet, it is the perceptions of their online information environments that ultimately shape individuals' relationships with people that hold opposing political views. Consider the following example from our survey that highlights the potential impact that perceptions have for enhancing emotional responses based on diverging political views. Our data show that people who *overestimate* their conservative (liberal) Twitter friends would be significantly more happy (unhappy) if their child would marry a Trump supporter *independently* of their own political alignment and the actual alignment of their Twitter environment (Appendix S10). This example thus illustrates how perceptions of a social environment – independently of the actual online content the individuals consume – are correlated with emotional responses towards those that do not align with an individual's own political views. And it also clearly highlights how it is not sufficient to consider information diets but, rather, that it is individuals' perceptions that ultimately matter.

In analyzing perceptions of politically slanted information environments, we leveraged an innovative approach for the comparison of Twitter users' perceptions to observed features of their online social network. 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. Bail et al. (2018), for example, find that following content of the opposite political side increases polarization, cautioning against strategies that simply suggest a diversification of news diets. More research is needed that looks specifically at the relationship between perceptions of news diets and the normative intentions of the consumers. This study though is the first to be able to provide unique insights into Twitter users' perceptions of the political slant of their surrounding and how these perceptions are influenced by their own political identities. We further demonstrated that active interest in ongoing political affairs is positively related to a better awareness of one's political Twitter diet. General political knowledge is certainly no panacea but our findings suggest that interventions that prompt users to be more aware of the characteristics of their online environments may help reduce harms associated to their online activities on social media platforms.

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