

Of Echo Chambers and Contrarian Clubs: Exposure to Political Disagreement Among German and Italian Users of Twitter

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Abstract

Scholars have debated whether social media platforms, by allowing users to select the information to which they are exposed, may lead people to isolate themselves from viewpoints with which they disagree, thereby serving as political “echo chambers.” We investigate hypotheses concerning the circumstances under which Twitter users who communicate about elections would engage with (a) supportive, (b) oppositional, and (c) mixed political networks. Based on online surveys of representative samples of Italian and German individuals who posted at least one Twitter message about elections in 2013, we find substantial differences in the extent to which social media facilitates exposure to similar versus dissimilar political views. Our results suggest that exposure to supportive, oppositional, or mixed political networks on social media can be explained by broader patterns of political conversation (i.e., structure of offline networks) and specific habits in the political use of social media (i.e., the intensity of political discussion). These findings suggest that disagreement persists on social media even when ideological homophily is the modal outcome, and that scholars should pay more attention to specific situational and dispositional factors when evaluating the implications of social media for political communication.

Keywords

social media, political discussion, political homophily, political disagreement, political networks

Introduction

Democracy is founded on freedom of public opinion (Manin, 1997), and for opinions to be freely formed, citizens need diverse but reliable sources of information (Dahl, 1998). At the same time, the likelihood that individuals encounter diverse and reliable viewpoints depends on their informational environments (Prior, 2007). Whereas research suggests that the mass media are more likely to expose individuals to diverse information in comparison with face-to-face discussions, scholars have debated whether digital media, because of their choice-enhancing affordances, are more conducive to self-segregation. In this article, we investigate the role of social media in exposing individuals to different viewpoints on the basis of unique representative online surveys of Twitter users who posted campaign-related messages during the general elections of 2013 in Germany and Italy.

We demonstrate that the Twitter users we sampled were more likely to employ social media to engage with networks that supported rather than challenged their views, but that

disagreement persisted on social media even when homophily was the modal outcome. The more individuals exchanged election-related messages on social media, the more likely they were to be part of networks that supported their views. At the same time, the ideological composition of respondents’ online networks closely reflected their face-to-face networks, so individuals encountering oppositional and mixed political viewpoints offline tended to have similar experiences on social media. We also show that, when online

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and offline experiences with agreement or disagreement do not perfectly overlap, political networks on social media are more likely to add to, rather than detract from, the overall diversity of political viewpoints that individuals encounter.

Taken together, our findings suggest that political homophily on social media is not a universal outcome that all users experience to an equivalent degree. On the contrary, it is a condition that citizens experience with different degrees of intensity depending on their broader patterns of political conversation and their specific habits in the political use of social media. In particular, individuals experiencing homophily in their offline discussion networks, and those who are more engaged in the exchange of political messages on social media, are more likely than others to encounter echo chambers on these platforms.

Antecedents to the Experience of Political Homophily on Social Media

In this study, we focus on two main themes: the extent to which social media foster exposure to political agreement or disagreement and the extent to which, and reasons why, individuals vary in their experience of political agreement and disagreement on social media. In particular, we assess whether social media users are prone to engage with three different types of political networks, as defined by Nir (2011): “supportive” networks, which primarily expose individuals to viewpoints with which they agree; “oppositional” networks that primarily confront members with viewpoints with which they disagree; and “mixed” networks that feature both congruent and divergent positions.¹

Political Agreement and Disagreement on Social Media

In contemporary media environments, citizens acquire and integrate political information received through interpersonal communication, the mass media, and digital media. Prior research suggests that these channels are not equally likely to expose individuals to diverse viewpoints. Studies of interpersonal communication show that individuals gravitate toward others who share their viewpoints (Huckfeldt & Sprague, 1995). This pattern has been understood within the rational choice paradigm as a strategy to acquire low-cost information from reliable sources (Downs, 1957) and within experimental social psychology as the result of individuals’ desire for belief confirmation (Festinger, 1957; Sears & Freedman, 1967). However, Huckfeldt, Johnson, and Sprague (2004) demonstrate that disagreement still persists, especially in low-density networks in which individuals interact with “weak ties,” that is, relatively distant acquaintances who are more likely to differ from them, in comparison with close interaction partners. Huckfeldt et al. (2004, pp. 21-23) also note that individuals choose with whom they talk not only on the basis of political homogeneity but also in terms of commonalities in lifestyles, hobbies, and family life.

The literature on selective exposure highlights that individuals, if given the opportunity, tend to choose media content that matches their political preferences (Garrett, 2009; Lazarsfeld, Berelson, & Gaudet, 1944) and that the mass media provide more exposure to contradictory viewpoints when compared with interpersonal conversations (Mutz & Martin, 2001). However, Iyengar and Hahn (2009) have shown that, in a high-choice media environment, citizens can craft personalized news diets that are consistent with their political views.

With respect to digital media, three different lines of research can be identified within the literature: (a) studies showing how the affordances of the Internet, by enhancing opportunities for the selection of sources, facilitate ideological self-segregation; (b) studies showing this type of selectivity, while resulting in increased exposure to consonant contents, does not necessarily lead to avoidance of dissonant ones; and (c) studies contending that inadvertent exposure to political content on the web might act as a counter-balancing mechanism increasing exposure to political disagreement.

The first strand of research emphasizes that the Internet’s selective nature—the fact that it allows, and to some degree compels, users to make frequent choices among a variety of sources and content (Bimber & Davis, 2003)—leads most individuals to engage primarily with views similar to their own. The general argument is that the Internet functions as an “echo chamber” in which individuals are exposed more or less exclusively to consonant views, and it is supported by some empirical research. Gaines and Mondak (2009) found that students in a large American university clustered on Facebook according to their ideological proclivities. Bakshy, Messing, and Adamic (2015) studied 10 million Facebook users in the United States who declared their ideological preferences and showed that—even taking into account the fact that Facebook’s algorithmic ranking of news according to users’ preferences limits the diversity of content they are exposed to—individuals are more likely to engage with stories that are consistent with their viewpoints. Studies analyzing large quantities of behavioral data likewise suggest that political networks on Twitter exhibit high levels of homophily (Barberá, 2015; Colleoni, Rozza, & Arvidsson, 2014; Conover et al., 2011). At the same time, Barberá, Jost, Nagler, Tucker, and Bonneau (2015) observed that the degree of homophily in information sharing on Twitter varied to a considerable extent according to users’ ideology, context, and issue type.

The second group of studies suggests that the choice affordances of digital media are less likely to produce self-segregation, such as the filtering out of dissonant viewpoints, in comparison with traditional forms of media. Based on extensive research, Holbert, Garrett, and Gleason concluded that the extent to which people deliberately avoid attitude-discrepant information online had been exaggerated by previous research. To the contrary, they argue, “individuals exhibit a stronger bias toward attitude-consistent information

than against attitude-discrepant information” (Holbert, Garrett, & Gleason, 2010, p. 19). In other words, political interactions on digital media may entail increased exposure to viewpoints users agree with, but not necessarily an equivalent avoidance of contrary ideas, and thus do not necessarily result in self-segregation.

Finally, according to the third line of research, even if individuals select online content and sources based on their political inclinations, digital media also facilitate exposure to different viewpoints, perhaps inadvertently. Given that individuals are more likely to come across attitude-discordant political content (often unintentionally) in non-political online environments than in overtly political spaces (Wojcieszak & Mutz, 2009), social media—insofar as it is often used for non-political reasons—may enable serendipitous exposure to views that are quite different from one’s own. Gil de Zúñiga and Valenzuela (2011) show that social media facilitates fortuitous contact with weak ties, which is likely to expose individuals to different political views. With respect to Twitter, Colleoni et al. (2014) suggest that the connections users build between each other exhibit high degrees of homophily, but information can also circulate across different networks and, in the process, expose individuals to dissonant viewpoints (see also Barberá et al., 2015).

Given that most of the literature suggests that individuals are more likely to seek agreement than disagreement on social media, we expect political homophily to be prevalent on social media. Thus, we hypothesize that in general *individuals are more likely to engage with supportive than oppositional or mixed networks on social media* (H1).

Nevertheless, the literature also provides some evidence that, under certain circumstances and for certain kinds of users, political networks on social media may differ from the modal outcome of homogeneity. However, research on what these factors are and under what conditions they operate has been very limited so far. Although most studies assume that conversations on social media are characterized by some degree of user control, scholars have generally failed to study how different users employ control affordances, and what implications such choices may have. This is because most scholars have treated important aspects of social media usage as constants rather than variables. To address this gap in the literature, our next hypotheses move beyond a general assessment to address how different individual-level characteristics may explain variation in exposure to supportive versus contrarian viewpoints on social media.

The Nexus Between Online and Offline Patterns of Political Discussion

We proceed from the premise that the role of social media in fostering or forestalling exposure to a diversity of political opinions cannot be understood without considering the specific goals and circumstances of different individuals’ social media activity as well as their broader patterns of political

conversation. This is because (a) social media are fundamentally intertwined with offline dynamics and (b) social media are high-choice environments in which individuals to some extent choose their levels of engagement with politics and the kinds of contents and sources they encounter.

Political networks on social media do not exist in a vacuum; they are part of a broader ecosystem of information flows in which individuals play different roles and exercise different degrees of agency. According to Chadwick (2013), contemporary political communication systems must be understood as “hybrid,” that is, combining different logics from older and newer media as well as integrating face-to-face and digital modes of engagement. This model implies that we cannot consider social media as separate from, or independent of, face-to-face conversational contexts—as most prior research has done—and that if we are to understand the role of social media in facilitating encounters with viewpoints that are dissonant versus consonant, we must take into account individuals’ offline discussion networks as well. Accordingly, research shows that individuals often use social media to connect (and reconnect) with members of their extended offline social networks (Ellison, Steinfield, & Lampe, 2007; Subrahmanyam, Reich, Waechter, & Espinoza, 2008). It is thus reasonable to expect that individuals’ patterns of offline conversation may be largely reproduced on social media, especially insofar as online interactions involve the same partners as face-to-face encounters.

Moreover, investigating the nexus between online and offline networks of political discussion helps to illuminate the various ways in which individuals approach political discussions in general. The “uses and gratifications” theory contends that individuals take advantage of the affordances of any medium of communication to fulfill their needs and preferences (Campbell & Kwak, 2010; Cho, Gil de Zúñiga, Rojas, & Shah, 2003). Taking offline networks into account when assessing online networks not only allows researchers to compare communication experiences in two different domains and platforms, it also facilitates an understanding of how given individuals differ in their overall approaches to political discussion writ large.

Finally, the extent to which individuals discuss politics—and the networks they develop—may be a function of their psychological characteristics, among other things. For instance, it is well known that individuals differ considerably in the extent to which they value openness to new experiences—as opposed to the preservation of what is familiar and traditional—and the extent to which they exhibit open-mindedness in the context of opinion exchange (e.g., Kruglanski, Webster, & Klem, 1993; McCrae, 1996; Rokeach, 1960; Schwartz, 2012). There is some evidence that these individual differences manifest themselves in terms of online behavior: people who score higher on openness tend to have larger and more diverse social media contacts and networks (Bachrach, Kosinski, Graepel, Kohli, &

Stillwell, 2012; Gosling, Augustine, Vazire, Holtzman, & Gaddis, 2011).

The hybridization of political communication, the uses and gratifications theory, and research on personality and social psychology all suggest that some degree of concordance is to be expected when it comes to the degree of ideological homophily in individuals' face-to-face and social media networks. Thus, we hypothesize that *the political composition of discussion networks that individuals engage with on social media is similar to the composition of their offline networks* (H2). Understanding the connections between face-to-face and online environments is also critical to assessing whether and under what circumstances the use of social media increases or decreases the overall diversity of political information to which one is exposed.

Political Habits on Social Media and Experience With Agreement and Disagreement

Once these individual circumstances and dispositions have been taken into account, we also need to consider how specific habits in the political use of social media may affect the likelihood that users encounter either agreement or disagreement on these platforms. In a high-choice media environment, people are likely to be selective when it comes to political content they are exposed to and with whom they discuss such content, and this selectivity is likely to be greater for those who are high (vs. low) in the intensity with which they engage with politics on social media. This is because the sheer abundance of potential content and interaction partners makes it not only possible, but also necessary, for individuals who are highly engaged in politics to filter out truly divergent perspectives. The more an individual is exposed to political content and engages in political discussion, the more rational it is for him or her to filter messages in order to maximize utility while minimizing effort. Selecting predominantly like-minded sources and conversational partners is clearly one way of attaining efficiency in this regard. Moreover, the intensity of political discussion is likely to be a reliable indicator of the strength of political identification and discursive involvement.

The theory of motivated reasoning suggests that people tend to search for information that reinforces their preexisting opinions and to avoid information that challenges them (Lodge & Taber, 2000; Stroud, 2008). The more involved in politics a given individual is, the more likely it is that he or she wishes to be part of an ideological community and, thus, to exercise selectivity in the context of social networks. Lawrence, Sides, and Farrell (2010) noted that most U.S. political blog readers—who are generally quite politically engaged—gravitate toward blogs that reinforce their own ideological inclinations, whereas very few read blogs across the entire ideological spectrum. Those who are highly involved in political discussions on social media may also be more likely to engage with like-minded others. Therefore,

we hypothesize that *the quantity of political messages that individuals exchange on social media is positively associated with the likelihood of engaging with supportive political networks on these platforms* (H3).

Case Selection

Most studies of online discussion networks have focused on the United States. This means that we cannot be sure whether findings from these studies can be generalized to other Western democracies. We address this omission by focusing on Germany and Italy—two large, relatively affluent European democracies that held general elections in 2013 and possess similar levels of Twitter diffusion (9% in Italy, 7% in Germany).² Unlike the United States, both Italy and Germany are parliamentary multiparty systems with mixed, but predominantly proportional, electoral laws. Although they differ from each other in some key respects—such as mean levels of political trust and the relative stability of party systems and governments—we do not expect these differences to bear on the structure and function of online political networks. It should be noted, given the goal of this research, that in multiparty systems it is often the case that parties pursue niche, bonding strategies aimed at mobilizing relatively narrow segments of the population (Norris, 2004, pp. 100-101). As a result, European citizens' ideological preferences may be more fragmented and multidimensional in comparison with citizens of majoritarian systems such as the United States.

In testing our hypotheses in Germany and Italy, we want to assess the robustness of our findings across different national systems and to expand existing knowledge beyond singular case studies of the United States.

Data

Investigating political discussions on social media requires that we focus on those individuals who take part in such discussions rather than on the entire voting-age population or even social media users in general. We focus on Twitter because it is one of the most popular social media platforms worldwide and its structure makes it especially germane to our hypotheses, insofar as it facilitates serendipitous encounters with unanticipated information and is highly accessible to study, because most of the interactions can be retrieved and archived. Testing our hypotheses requires valid and reliable measures of the political activities performed by social media users, what motivates them, and what kinds of information they encounter. We, therefore, devised unique surveys of representative samples of individuals who engaged in election-related conversations on Twitter in Germany and Italy. Compared with analyses of behavioral data of individuals' interactions on social media, surveying representative samples of these users allows us to measure constructs, such as characteristics of face-to-face interactions, which may not be

observable on the basis of social media activities alone. The potential downside is that our results could be an artifact of the extent that respondents systematically misreport characteristics of online and offline networks.³ Moreover, as with all cross-sectional surveys, our data are subject to some degree of endogeneity and, therefore, do not support causal interpretations of claims regarding the associations we observe.

Sampling Political Users of Twitter

Because no comprehensive list of Twitter users—let alone, Twitter users who discuss elections—is publicly available, we devised a strategy to construct sampling frames that are as inclusive as possible with respect to our populations. Because most of the sources and messages posted by Twitter users are publicly accessible,⁴ we rely on the contents of these messages to identify our populations, which we define as those Twitter users who posted messages concerning the German and Italian elections of 2013. We pinpoint these users on the basis of election-related keywords—the names of the main parties, their leaders, and the topical hashtags for the elections⁵—contained in the messages they posted. We used these keywords to query Twitter’s Streaming API during each country’s extended campaign season⁶ and retrieved about 5.8 million tweets from over 151,000 unique users in Germany and 3 million tweets from over 275,000 unique users in Italy.⁷

Fielding a Survey of Twitter Users

From these lists of users, we randomly selected 43,000 users in Germany and 35,000 in Italy and contacted them via Twitter through an automated script that delivered a personalized message as follows: “[@username] University research on social media use: Would you like to participate? [link to the survey].”⁸ Because our invitations were delivered in such a way that recipients were asked to share their opinions with strangers via social media, respondents to our surveys may differ from those who refused to answer in terms of their willingness to express their opinions to strangers. People who are more open to engaging with strangers on social media might also be more likely to encounter disagreeing opinions on these platforms. As a result, it is possible that our sample may overestimate exposure to political disagreement online. Although we acknowledge this potential bias, we emphasize that it works against our first and third hypotheses (see above), while it does not affect our ability to validly test our second hypothesis. In sum, we have no reason to believe that our findings are an artifact of the method we chose to contact our respondents.

A total of 1,143 (Germany) and 1,493 (Italy) individuals answered at least half of the questions, which corresponds to response rates of 4%.⁹ Because these are by no means high figures—although they are not much lower than the single-digit response rates that are common in telephone

surveys¹⁰—in Appendices B and C¹¹ we illustrate evidence suggesting that our respondents may be considered representative of Germans and Italians who discussed the 2013 elections on Twitter, and that the differences that could be measured between these two groups were taken into account in our analysis.¹²

Political Users of Twitter Versus General Population Samples

Understanding the behaviors of representative samples of Twitter users who commented on their countries’ elections enables us to understand political communication on social media platforms and the factors that shape it (see Bekafigo & McBride, 2013 and Bode & Dalrymple, 2014, for other representative surveys of Twitter users). At the same time, focusing on the specific population of individuals who posted at least one election-related tweet does not allow us to generalize to other populations, such as citizens who read (but do not post) political messages on Twitter. To the extent that our survey respondents were more engaged in politics than the general population, we would expect—on the basis of prior research (e.g., Mutz, 2006)—that they would be less eager to engage with contrary views; we take this possibility into account by controlling for relevant political attitudes in our analyses.¹³

Variables

Although our respondents were recruited via Twitter, our primary independent and dependent measures focus on general social media use because individuals’ online interactions, political and otherwise, are not limited to one platform, but often integrate many of them: For instance, a person can use Twitter to share a YouTube video, a Facebook status update, or an Instagram picture. When we asked respondents to indicate social networking platforms on which they had a profile, the median respondent had profiles in 4 of 10 platforms we asked about in Italy and 5 of 10 in Germany.

Our dependent variables measure the types of political networks that individuals engage with on social media, in response to two questions: “How often do you [agree/disagree] with the political opinions and contents that other people post on social media?” Respondents could answer with one of four categories:

- *Always or nearly always* (4% of German and 0.6% of Italian respondents for agreement; 1% of Germans and 0.8% of Italians for disagreement);
- *Often* (43.1% of German and 42.4% of Italian respondents for agreement; 18.1% of Germans and 21.8% of Italians for disagreement);
- *Only sometimes* (50.3% of German and 55.9% of Italian respondents for agreement; 77.8% of Germans and 76.3% of Italians for disagreement);

- *Never* (2.6% of German and 1.1% of Italian respondents for agreement; 3.1% of Germans and 1.1% of Italians for disagreement).

As Nir (2011) showed, mixed political networks have important implications for political engagement, and should thus not be treated simply as an intermediate category between supportive and oppositional ones. This is why we use as dependent variables dichotomous measures representing each of these types of networks rather than a combined ordinal measure of the continuum of supportive, mixed, and oppositional networks. Because only about 5% of respondents used the most extreme categories, we combined the first two and the last two response categories and then constructed a composite measure corresponding to four types of network structures:

- Respondents who claimed to always or often encounter agreement and rarely or never disagreement were classified as participating in *supportive* networks;
- Respondents who claimed to always or often encounter disagreement and rarely or never agreement were classified as participating in *oppositional* networks;
- Respondents who claimed to always or often encounter both agreement and disagreement were classified as participating in *mixed* networks,
- Respondents who claimed to rarely or never encounter agreement or disagreement were classified as participating in *neutral* networks.¹⁴

The independent variables required to test our hypotheses involve the characteristics of respondents' offline political networks (H2) and the proportion of political messages they exchange on social media (H3).

We test H2 by focusing on responses to the questions "How often do you usually [agree/disagree] with the opinions of people with whom you talk about politics?" These questions immediately followed a specific question about how frequently respondents discussed politics in face-to-face contacts with friends and family. The response modes were the same as for the questions about social media, and we derived combined measures of supportive (36.5% of German and 34.8% of Italian respondents), oppositional (16.6% of German and 25.2% of Italian respondents), mixed (8.6% of German and 8.2% of Italian respondents), and neutral (38.3% of German and 31.8% of Italian respondents) offline networks in the same ways as we did for social media networks.

We test H3 by averaging answers to two separate questions, one for posting and one for reading political messages. The questions were: "Thinking about everything you have recently [posted/read from people you follow or are in contact with] on social media, such as status updates, comments, or links to news stories—about how much is related to politics, political issues or the 2013 elections?"

Respondents could answer both questions by indicating a number between 0 (none) and 10 (all).¹⁵ The resulting variable averaged 4.46 ($SD = 2.58$) for the German and 4.46 ($SD = 2.27$) for the Italian sample.

Findings

Bearing on H1, Figure 1 shows the percentages of German and Italian respondents who engage with supportive, oppositional, mixed, and neutral political networks on social media. Respondents are substantially more likely to engage with supportive rather than oppositional networks (40.6% vs. 12.5% in Germany and 35.8% vs. 15.3% in Italy), and in both cases, the differences are statistically significant.¹⁶ Participation in networks that exhibit disagreement with respondents' opinions is not, however, infrequent: In both countries, oppositional and mixed networks (combined) affect one in five respondents—one in three if we exclude those in "neutral" networks that are disengaged from politics. These findings support H1, insofar as respondents on average encounter more agreement than disagreement, but they also suggest that for some people, social media platforms are not "echo chambers" of univocal agreement, but "contrarian clubs" where political disagreement is common. Another interesting finding is that about two in five of our respondents participate in networks in which no particular political opinions emerge, and this group is the modal one in the Italian sample. Thus, even among those social media users who communicated at least once about the election, exposure to very few political opinions is approximately as likely as exposure to attitude-congruent opinions.

We address our remaining hypotheses by conducting three logistic regressions (summarized in Table 1)¹⁷ that, in each country, predict whether respondents report being part of supportive, oppositional, or mixed political networks on social media as a function of the characteristics of their offline political networks (H2), and the proportion of political messages they exchange on social media (H3).

The models include control variables for socio-demographic characteristics,¹⁸ political attitudes (political efficacy, interest in politics, and trust in political parties), frequency of offline political discussion, and frequency of use of different media to get political information. We also control for respondents' preferred use of social media, distinguishing between those who claimed to consider social media to be more important for finding people with similar (vs. different) viewpoints, in comparison with their own.¹⁹ We introduced this variable in accordance with the "uses and gratification" theory, which contends that individuals' preferences may shape the type of conversational experiences they have on social media. Controlling for respondents' preferred use of social media provides a more precise assessment of the specific role played by broader patterns of political conversation as well as habits in the political use of social media when it comes to the development of citizens' online networks.²⁰

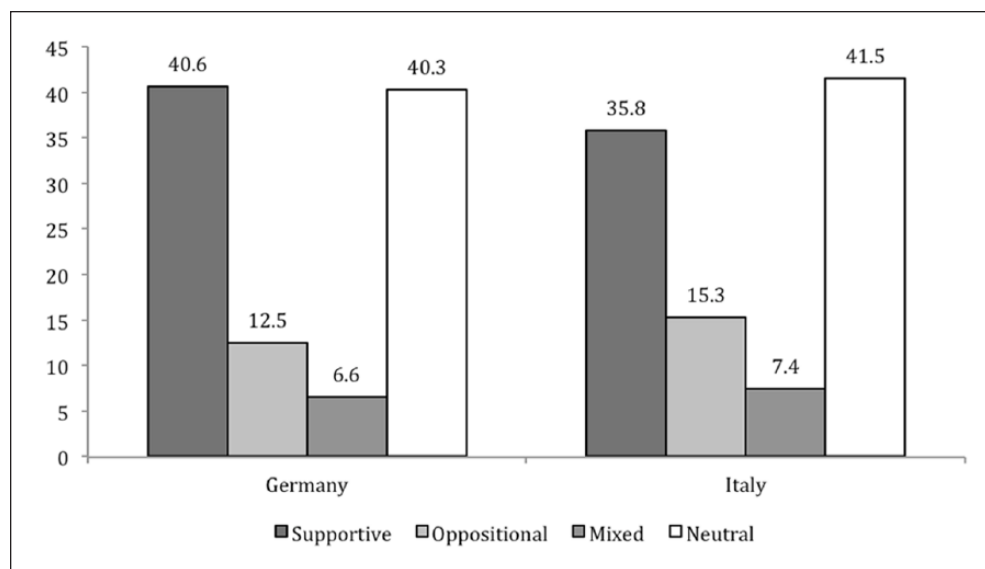


Figure 1. Engagement with different types of political networks on social media (percentages among country respondents).

Note. Percentages based on self-reports, see text for coding of responses on network political agreement and disagreement into reported categories. Paired samples two-tailed *t* test gave the following results: supportive versus mixed networks $t = 11.782$ ($p = .000$) in Germany and $t = 10.565$ ($p = .000$) in Italy; supportive versus mixed networks $t = 15.386$ ($p = .000$) in Germany and $t = 16.515$ ($p = .000$) in Italy; oppositional versus mixed networks $t = 2.945$ ($p = .009$) in Germany and $t = 5.843$ ($p = .000$) in Italy; neutral versus supportive networks $t = -0.101$ ($p = .920$) in Germany and $t = 2.371$ ($p = .018$) in Italy; neutral versus oppositional networks $t = 8.081$ ($p = .000$) in Germany and $t = 13.077$ ($p = .000$) in Italy; neutral versus mixed networks $t = 13.234$ ($p = .000$) in Germany and $t = 19.609$ ($p = .000$) in Italy.

As can be seen from the first block of coefficients in Table 1, H2 is supported in both countries, insofar as we see positive and significant associations between all relevant pairs of independent and dependent variables. As an example of the strength of these associations, if we construct a hypothetical Italian respondent that has values equal to the median (for interval and ordinal variables) or modal (for categorical variables) values in the sample, then the probability that this hypothetical (male) respondent would engage with supportive political networks on social media is 48% if he also engages with supportive offline networks, but only 26% if he engages with either mixed, oppositional, or neutral offline networks. The results also highlight some interesting differences between the two countries. While in Germany respondents who engage with oppositional networks offline are significantly more likely to encounter either oppositional or mixed networks online, in Italy engagement with offline oppositional networks is solely associated with oppositional networks on social media. By contrast, whereas in Germany those who engage with mixed offline networks are more likely to engage with the same types of networks on social media, in Italy those who are part of mixed offline networks are significantly more likely to interact with either oppositional or mixed networks on social media. Individuals' online and offline experiences tend to overlap, but to the extent that they do not overlap perfectly, social media functions as an echo chamber only for those individuals who also possess homogeneous offline networks. Another way to interpret these associations is that political networks on social media are

more likely to add to than detract from the overall diversity of political viewpoints to which individuals are exposed.²¹

The data also support H3, namely the expectation of a positive association between the intensity of online political involvement and the probability of participating in supportive networks.²² In both countries, the more individuals post and read political messages on social media, the more likely they are to engage with supportive networks. As an example, if we set all variables to their median or modal levels in the German sample, a hypothetical respondent has a 39% probability of engaging with a supportive network. If, however, the intensity of his or her activity is increased to one standard deviation above the median, the probability of engaging with supportive networks increases to 49%. Conversely, if the intensity of his or her activity is set one standard deviation below the median, the probability of engaging with supportive networks decreases to 30%.

Finally, the associations pertaining to the control variable measuring preferences for political agreement versus disagreement on social media deserve a brief comment. In both countries, respondents who attribute greater importance to social media for encountering agreement as opposed to disagreement (positive values of the variable) are significantly more likely to engage with supportive networks on these platforms. To the contrary, the association between such variable (where respondents valuing social media as more important for encountering disagreeing than agreeing others have negative values) and engagement with oppositional views is negative in both countries, but it is significant only

Table 1. Dependent Variable(s): Types of Political Networks Respondents Engage With on Social Media.

	Germany			Italy		
	Supportive	Oppositional	Mixed	Supportive	Oppositional	Mixed
Face-to-face political networks (ref. neutral)						
Supportive	0.818**	-0.201	0.832	0.998***	0.183	0.580
Oppositional	-0.381	0.899*	1.200*	0.040	1.756***	0.228
Mixed	-0.365	0.489	1.696**	0.032	1.082**	2.072***
Ratio of political messages on the total exchanged on social media	0.153***	-0.041	0.149	0.120**	-0.058	0.126
Preferred use of social media	1.240**	-1.032	0.224	1.714***	-1.056*	-0.675
Source of political information						
Internet	0.078	1.023	-0.386	0.171	-0.488	-0.983
Newspapers	-0.460	0.360	-0.167	-0.690*	0.060	-0.433
Radio	-1.046***	0.612	0.562	-0.508*	0.005	0.815
Television	-0.406	-0.264	-0.008	0.078	-0.068	0.911
Political efficacy (disagreement with following sentences)						
“People don’t have any say”	0.108	-0.201	-0.581	0.042	0.469	-0.048
“Public officials don’t care”	0.167	-0.375	0.849	0.338	-0.239	-0.886
“Politics is too complicated”	-0.660	-0.039	0.799	-0.098	0.000	0.311
Interest in politics	1.601**	-0.923	0.846	-0.141	0.805	1.969
Trust in political parties	-0.276	-0.641	0.597	0.379	-0.386	-0.768
Offline political discussion (frequency)	0.079	0.661	-0.118	0.257	-1.014	-0.587
Gender (male)	-0.128	-0.227	0.367	-0.211	0.041	0.212
Age	-0.712	-1.051	-0.401	-0.561	-0.347	-0.798
Education	-0.431	1.025	-1.042	0.361	0.290	0.614
Income	-0.582	1.421	0.812	-0.094	0.227	-0.528
Constant	-0.667	-3.087**	-5.569***	-1.348**	-1.893**	-4.822***
N	727	727	727	1,167	1,167	1,167
Percentage correctly predicted	69.9	86.5	93.4	68.7	85.1	93.4
Nagelkerke R^2	.241	.125	.141	.164	.157	.143
Log-likelihood	834.045	518.951	312.860	1,391.319	889.100	503.732

Note. Cell entries are estimated logit coefficients where the dependent variable is 1 for the reported network type, and all other network types are coded as 0. See Appendices E to J for complete results with standard errors. Dummy variable identifying missing observations for income omitted from table, see note 18. All variables range from 0 to 1 apart from political messages exchanged (0-10) and preferred use of social media (-1 to 1, with respondents who claimed that agreement was more important than disagreement having positive values, whereas those who stated that disagreement was more important than agreement having negative values, and those who attributed equal importance to agreement and disagreement having a score of zero).

*** $p \leq .001$. ** $p \leq .01$. * $p \leq .05$.

in Italy. This pattern may suggest that, for individuals who approach social media deliberately in search of agreement (vs. disagreement), it may be relatively easy to obtain such agreement. Instead, for those preferring to seek out disagreement, it may be more difficult to locate and participate in “contrarian clubs.”

Conclusion

We have shown that German and Italian Twitter users who communicate about elections are more likely to do so in networks that support rather than challenge their views, consistent with the notion that social media facilitates the emergence of echo chambers. At the same time, contrarian clubs, which involve frequent encounters with dissonant opinions—whether in oppositional or mixed networks—are less exceptional than expected. We may have come across an important parallelism between studies of political communication

offline and online: As noted by Huckfeldt et al. (2004) with respect to offline networks, heterogeneity persists on social media even though homogeneity is the modal outcome.

We have approached citizens’ experiences with political agreement and disagreement on social media through the theoretical lenses of hybridization in political communication and of “uses and gratifications” theory, while at the same time taking into account the importance of individual attitudes in high-choice media environments. This, in turn, led us to focus on aspects that are likely to differentiate individuals, as opposed to treating everyone as guided by technological affordances in the same way. Thus, we have been able to demonstrate that the extent to which social media functions as an echo chamber (as opposed to a contrarian club) varies across individuals. This, in turn, suggests that understanding political dynamics in choice-enhancing platforms may be better served by an appreciation that different users have different traits, preferences, and social networks that affect

their behaviors and experiences rather than an assumption that most or all users employ the selective features of social media to pursue the same goals, thus leading to fairly predictable and monolithic outcomes.

More specifically, we hope to have shed light on broader dynamics of political communication as well as specific habits pertaining to the political use of social media that help to explain how various platforms give rise to different types of political networks. Our observation that online and offline networks tend to resemble one another suggests that understanding the dynamics of political communication requires a holistic approach that encompasses both contexts. As increasing numbers of citizens rely on social media for political information, which they often encounter by discussing public affairs with others, the overall diversity of viewpoints in contemporary democracies is not likely to be dramatically reduced when compared with face-to-face discussions; in some cases, it may even be broadened. However, the use of social media seems to diminish political diversity for those who participate in more or less entirely supportive offline networks and who prefer engaging with people with whom they tend to agree.

At the level of individual behavior online, our finding that the more people post and read political messages on social media, the more likely they are to encounter supportive networks indicates that, all else being equal, the greatest proportion of social media messages exchanged involve interactions among individuals who agree with one another. This highlights a crucial methodological issue in the study of online political communication. To the extent that the quantity of *messages and interactions* that can be observed on social media is associated with the levels of agreement *among individuals* who take part in these exchanges, scholars interested in the implications of social media for political diversity should be aware that taking messages or connections as their unit of analysis may overestimate the pervasiveness of homogeneity *as actually experienced by individuals*.

Finally, our study has confirmed the centrality of hybridity in contemporary environments of political discussion. Building on Chadwick's (2013) theorizing, we have investigated the relationship between newer (i.e., social media) and older (i.e., face-to-face) networks of political discussion, and have observed that these two types of environments—and their underlying logics—are integrated rather than separated. Our findings also have important implications for power—a crucial component of Chadwick's theory—insofar as they suggest that politically active citizens will be unlikely to find much challenging content on social media, but they may be able to reach less engaged users—who according to our findings are less likely to be part of exclusively homophilic networks—with oppositional points of view. Under certain conditions, these interactions could create opportunities for political persuasion and, thus, the possibility for some to exercise influence over others.

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Notes

1. Networks can also be "neutral" to the extent that members are not exposed to substantial levels of agreement or disagreement—a category that we treat as residual for the purposes of this study.
2. See <http://wearesocial.net/blog/2014/01/social-digital-mobile-worldwide-2014/> (accessed 31 July 2014). We are aware that these figures indicate low usage rates in the two countries. However, even in countries where Twitter rates are higher, such as the United States (around 17% of Americans used Twitter in 2014), usage rates are still rather limited. Therefore, as we seek to clarify in the subsection "Political users of Twitter versus general population samples," we do not claim that our findings are generalizable to populations others than political users of Twitter in the two countries. At the same time, we consider these samples useful for understanding online political networks.
3. We are aware that there may be social desirability bias in users' reported exposure to oppositional networks. However, observing users' behavior in engaging with disagreement on social media—even if limited to only one platform, that is, Twitter—would have required a very extensive exercise of data collection, which is outside the scope of this article, and still would have left us without any reliable measure of the characteristics of users' offline political networks, which is crucial to our theory and hypotheses. That being said, we believe the social desirability bias, to the extent it was present in our data, should not have substantially affected our findings.
4. The only messages that are inaccessible are those by users who "protect" their profiles, making their posts visible only to those who "follow" them. Because only 5% of Twitter accounts are protected (Liu, Kliman-Silver, & Mislove, 2014), our inability

to observe protected tweets should not substantially bias our findings.

5. The full list of keywords is reported in Appendix A.
6. Retrieval dates were 28 June 2013 to 22 September 2013 for Germany and 18 January 2013 to 28 February 2013 for Italy.
7. The fact that we spent more time crawling tweets for the German (vs. Italian) election explains why we have more tweets for the former. Because we used comparable search keywords, the numbers of unique users that we obtained for each country are consistent with Twitter diffusion rates.
8. Although these messages are technically public, because they were addressed specifically to the users in our samples, no one else on Twitter could see them unless they followed our account (which had no followers) or were searching based on keywords included in our message. Some addressees might have shared the link to our survey with other people and so, in principle, some users outside of our samples may have taken the survey. In the German survey, we asked respondents whether they had received a direct message from us and found that 94% reported that they did. We deleted from our data set all the information from respondents who had not received a direct invitation from us. Although we did not employ this control for the Italian survey, in a follow-up study, we found that 97% of respondents had received a direct personal invitation from us. Controls based on IP addresses ensured that the surveys could be answered only once from the same computer. Because we filtered the Italian, but not the German tweets by language, and because, unlike Italian, German is widely spoken abroad, we asked individuals contacted for the German survey whether they were German citizens or residents, and excluded the 39% who answered negatively. This percentage was quite high because the keywords we searched for are likely to be discussed outside Germany. For instance, the German chancellor is often featured in the news of most European Union countries due to her central role in European Union (EU) politics.
9. The surveys were in the field for about 2 months in Italy and 4 months in Germany. Such prolonged fieldwork was motivated by two considerations. First, logistical considerations forced us to limit the number of invitations we sent out each day. Second, we attempted to contact most respondents twice in order to increase the response rate.
10. For instance, Pew reported average 9% response rates for its telephone surveys in 2012. See <http://www.people-press.org/2012/05/15/assessing-the-representativeness-of-public-opinion-surveys/> (accessed 21 August 2014).
11. All Appendices can also be accessed at <http://webpoleu.altervista.org/wp-content/uploads/2013/09/SM+S-appendix-online-nw.pdf>
12. See also Vaccari et al. (2015) for a detailed description of the methods we employed to assess and improve the representativeness of our sample.
13. We did not measure respondents' partisanship because this concept has proved to be more difficult to measure, and less useful in the study of voting behavior, outside the United States and United Kingdom (see Holmberg, 2007). Also, we did not measure respondents' online and offline discussion network size, which is likely to be associated with the heterogeneity of the views they are exposed to (Gil de Zúñiga & Valenzuela, 2011).
14. By including respondents (coded as "0") who rarely or never encounter agreement or disagreement on social media, and who can thus be expected to be disengaged from political discussions, we may confound individuals' political networks with the frequency with which they discuss politics. We address this problem in our multivariate analyses by controlling for intensity of political discussion. Moreover, we tested alternative models in which respondents in neutral political networks were omitted rather than coded as "0." These models, reported in Appendix D, yield findings consistent with the results of the main models reported in Table 1.
15. In the Italian questionnaire, the scale ranged from 0 to 100, so we divided the values by 10 to make these variables comparable across countries.
16. $t=11.782$ ($p=.000$) in Germany and $t=10.565$ ($p=.000$) in Italy according to paired samples t tests (two-tailed).
17. Table 1 reports estimated logit coefficients. Full statistical information on our models is reported in Appendices E to J.
18. Because our income variable included a large proportion of missing data, rather than introducing bias through listwise deletion (King, Honaker, Joseph, & Scheve, 2001), we mean-replaced these missing values and added a dummy variable to the analysis to identify these cases. In this framework, the coefficient for any given variable with missing data should be interpreted as the effect of that variable on our dependent variable for the cases for which we have observations of the independent variable in question. We thank Larry Bartels for suggesting this approach. The coefficients for the dummy variables identifying the missing cases—which are essentially meaningless because they are simply a function of whatever value we use to replace the missing observations—are not included in the tables.
19. For question wording, response modes, and descriptive statistics related to all control variables, see Appendix K.
20. In Appendix L we show that all our findings hold even if we exclude this variable from the models.
21. As we show in Appendices M and N, these patterns are also revealed by bivariate analyses: For instance, 56% of Germans and 52% of Italians who engage with supportive networks offline also engage with supportive networks online.
22. As can be seen in Appendix D, when we excluded respondents in neutral networks, intensity of political discussion was positively but not significantly related with engagement with supportive networks, but it was negatively and significantly related with engagement with oppositional networks. We see this finding as the other side of the coin of the finding in our main models: In one case, the more intensely respondents discuss politics on social media, the more likely they are to do so with supportive networks; in the other case, the more intensely respondents discuss politics on social media, the less likely they are to do so with oppositional networks.

References

- Bachrach, Y., Kosinski, M., Graepel, T., Kohli, P., & Stillwell, D. (2012). Personality and patterns of facebook usage. Retrieved from http://research.microsoft.com/pubs/163535/FacebookPersonality_michal_29_04_12.pdf
- Bakshy, E., Messing, S., & Adamic, L. (2015). Exposure to ideologically diverse news and opinion on Facebook. *Science*. Advance online publication. doi:10.1126/science.aaa1160

- Barberá, P. (2015). Birds of the same feather tweet together: Bayesian ideal point estimation using Twitter data. *Political Analysis*, 23, 76–91.
- Barberá, P., Jost, J. T., Nagler, J., Tucker, J., & Bonneau, R. (2015). Tweeting from left to right: Is online political communication more than an echo chamber? *Psychological Science*, 26, 1531–1542.
- Bekafigo, M. A., & McBride, A. (2013). Who tweets about politics? Political participation of Twitter users during the 2011 gubernatorial elections. *Social Science Computer Review*, 31, 625–643.
- Bimber, B. A., & Davis, R. (2003). *Campaigning online: The Internet in US elections*. Oxford, UK: Oxford University Press.
- Bird, S., Klein, E., & Loper, E. (2009). *Natural language processing with Python*. Sebastopol, CA: O'Reilly.
- Bode, L., & Dalrymple, K. (2014). Politics in 140 characters or less: Campaign communication, network interaction, and political participation on Twitter. *Journal of Political Marketing*. Advance online publication. doi:10.1080/15377857.2014.959686
- Campbell, S. W., & Kwak, N. (2010). Mobile communication and civic life: Linking patterns of use to civic and political engagement. *Journal of Communication*, 60, 536–555.
- Chadwick, A. (2013). *The hybrid media system: Politics and power*. New York, NY: Oxford University Press.
- Cho, J., Gil de Zúñiga, H., Rojas, H., & Shah, D. V. (2003). Beyond access: The digital divide and Internet uses and gratifications. *IT & Society*, 1, 46–72.
- Colleoni, E., Rozza, A., & Arvidsson, A. (2014). Echo chamber or public sphere? Predicting political orientation and measuring political homophily in twitter using big data. *Journal of Communication*, 64, 317–332.
- Conover, M., Ratkiewicz, J., Francisco, M., Gonçalves, B., Menczer, F., & Flammini, A. (2011). *Political polarization on Twitter*. Proceedings of the ICWSM, Barcelona, Spain, 17–21 July.
- Dahl, R. (1998). *On democracy*. New Haven, CT: Yale University Press.
- Downs, A. (1957). *An economic theory of democracy*. New York, NY: HarperCollins.
- Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook “friends”: Social capital and college students’ use of online social network sites. *Journal of Computer-Mediated Communication*, 12, 1143–1168.
- Festinger, L. (1957). *A theory of cognitive dissonance*. Stanford, CA: Stanford University Press.
- Gaines, B. J., & Mondak, J. J. (2009). Typing together? Clustering of ideological types in online social networks. *Journal of Information Technology & Politics*, 6, 216–231.
- Garrett, R. K. (2009). Politically motivated reinforcement seeking: Reframing the selective exposure debate. *Journal of Communication*, 59, 676–699.
- Gelman, A., & Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. New York, NY: Cambridge University Press.
- Gil de Zúñiga, H., & Valenzuela, S. (2011). The mediating path to a stronger citizenship: Online and offline networks, weak ties and civic engagement. *Communication Research*, 38, 397–421.
- Gosling, S. D., Augustine, A. A., Vazire, S., Holtzman, N., & Gaddis, S. (2011). Manifestations of personality in online social networks: Self-reported facebook-related behaviors and observable profile information. *Cyberpsychology, Behavior, and Social Networking*, 14, 483–488.
- Holbert, R. L., Garrett, R. K., & Gleason, L. S. (2010). A new era of minimal effects? A response to Bennett and Iyengar. *Journal of Communication*, 60, 15–34.
- Holmberg, S. (2007). Partisanship reconsidered. In R. Dalton & H. D. Klingemann (Eds.), *The Oxford handbook of political behavior* (pp. 557–570). Oxford, UK: Oxford University Press.
- Huckfeldt, R., Johnson, P. E., & Sprague, J. (2004). *Political disagreement: The survival of diverse opinions within communication networks*. New York, NY: Cambridge University Press.
- Huckfeldt, R., & Sprague, J. (1995). *Citizens, politics and social communication: Information and influence in an election campaign*. New York, NY: Cambridge University Press.
- Iyengar, S., & Hahn, K. S. (2009). Red media, blue media: Evidence of ideological selectivity in media use. *Journal of Communication*, 59, 19–39.
- King, G., Honaker, J., Joseph, A., & Scheve, K. (2001). Analyzing incomplete political science data: An alternative algorithm for multiple imputation. *American Political Science Review*, 95, 49–69.
- Kruglanski, A. W., Webster, D. M., & Klem, A. (1993). Motivated resistance and openness to persuasion in the presence or absence of prior information. *Journal of Personality and Social Psychology*, 65, 861–876.
- Lawrence, E., Sides, J., & Farrell, H. (2010). Self-segregation or deliberation? Blog readership, participation, and polarization in American politics. *Perspectives on Politics*, 8, 141–157.
- Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1944). *The people's choice*. New York, NY: Columbia University Press.
- Liu, Y., Kliman-Silver, C., & Mislove, A. (2014). *The tweets they are a-Changin': Evolution of twitter users and behavior*. Palo Alto, CA: AAAI.
- Lodge, M., & Taber, C. (2000). Three steps toward a theory of motivated political reasoning. In A. Lupia, M. McCubbins, & S. Popkin (Eds.), *Elements of reason: Cognition, choice, and the bounds of rationality* (pp. 183–213). Cambridge, UK: Cambridge University Press.
- Manin, B. (1997). *The principles of representative government*. New York, NY: Cambridge University Press.
- McCrae, R. R. (1996). Social consequences of experiential openness. *Psychological Bulletin*, 120, 323–337.
- Mutz, D., & Martin, P. (2001). Facilitating communication across lines of political difference: The role of mass media. *American Political Science Review*, 95, 97–114.
- Mutz, D. C. (2006). *Hearing the other side: Deliberative vs. participatory democracy*. New York, NY: Cambridge University Press.
- Nir, L. (2011). Disagreement and opposition in social networks: Does disagreement discourage turnout? *Political Studies*, 59, 674–692.
- Norris, P. (2004). *Electoral engineering: Voting rules and political behavior*. New York, NY: Cambridge University Press.
- Prior, M. (2007). *Post-broadcast democracy: How media choice increases inequality in political involvement and polarizes elections*. New York, NY: Cambridge University Press.
- Rokeach, M. (1960). *The open and closed mind: Investigations into the nature of belief systems and personality systems*. New York, NY: Basic Books.
- Schwartz, S. H. (2012). An overview of the Schwartz theory of basic values. *Online Readings in Psychology and Culture*, 2, 1–11. Retrieved from <http://scholarworks.gvsu.edu/cgi/view-content.cgi?article=1116&context=orpc>
- Sears, D. O., & Freedman, J. L. (1967). Selective exposure to information: A critical review. *Public Opinion Quarterly*, 31, 194–213.

- Stroud, N. J. (2008). Media use and political predispositions: Revisiting the concept of selective exposure. *Political Behavior*, 30, 341–366.
- Subrahmanyam, K., Reich, S. M., Waechter, N., & Espinoza, G. (2008). Online and offline social networks: Use of social networking sites by emerging adults. *Journal of Applied Developmental Psychology*, 29, 420–433.
- Vaccari, C., Valeriani, A., Barberá, P., Bonneau, R., Jost, J. T., Nagler, J., & Tucker, J. A. (2015). Political expression and action on social media: Exploring the relationship between lower-and higher-threshold political activities among twitter users in Italy. *Journal of Computer-Mediated Communication*, 20, 221–239.
- Wojcieszak, M., & Mutz, D. (2009). Online groups and political discourse: Do online discussion spaces facilitate exposure to political disagreement? *Journal of Communication*, 59, 40–56.

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Appendix A

Keywords Employed to Retrieve Election-Related Tweets

Germany

Political parties

AFD

CDU

CSU

FDP

Grünen

Linke

Piratenpartei

SPD

Party leaders

Brüderle

Göring-Eckardt

Kipping

Lucke

Merkel

Riexinger

Rösler

Schlömer

Seehofer

Steinbrück

Trittin

Election hashtags

#btw2013

#Bundestagswahl2013

#wahl2013

Italy

Political parties

IDV

Lega

M5S

PD

PDL

Rivoluzione Civile

Scelta Civica

SEL

UDC

Party leaders

Berlusconi

Bersani

Casini
Di Pietro
Grillo
Ingroia
Maroni
Monti
Vendola

Election hashtags

#elezioni2013

Appendix B

Assessment of Sample Representativeness

In this section, we illustrate evidence suggesting that our respondents can be considered representative of Germans and Italians who discussed the 2013 elections on Twitter, and that the differences that could be measured between these two groups were taken into account in our analysis.

To substantiate this claim, we need to combine and compare information about our respondents and all the users we invited to take our surveys, and to achieve this goal we integrate our survey data with observations of Twitter activity. With regard to our respondents, we know their answers to our survey questions, but—at least for the majority of them—we do not know their social media activities (such as how often they posted messages, how many accounts they followed, and the like) because selection into our surveys was anonymous. With regard to all the users we invited to participate in our surveys, we know their social media activities because Twitter usage is public and we can measure this behavior regardless of whether or not someone chose to take our surveys, but we of course do not know how they would have answered our questions. However, approximately 40% of our respondents chose to provide us with their Twitter handle, so for this subsample we have both of these types of information: the answers to our survey questions *and* their behavior on Twitter. Thus, we can compare how similar this portion of our respondents are to all the users we invited to participate in our survey (based on Twitter activity) and how similar they are to respondents who did not give us their Twitter handles (via the survey data). We also employ a number of techniques developed by scholars to estimate characteristics of Twitter users such as gender, location, and ideology.

In particular, gender was estimated using a Naive Bayes classifier (Bird, Klein, & Loper, 2009) trained with a list of common Italian and German names and their gender, and then applied to the name of each Twitter user, as reported on their profile. We found that this technique is able to accurately classify the gender of 90% of Twitter users. Each user's location was identified by parsing the "location" field

in each profile using the Data Science Toolkit geocoder (<http://www.datasciencetoolkit.org>), which turns text into a set of coordinates, which we then matched to Italian and German regions. We were able to identify the region in which each user lives in 60% of cases in Italy and 51% of cases in Germany. Finally, ideology was measured using the "spatial following model" described in Barberá (2015), which estimates ideology based on the political actors and media outlets that each Twitter user follows. We found that this method is able to classify the self-reported ideological positions (left-right) of Italian respondents in our survey with 82% accuracy and of German respondents with 71% accuracy.

This information in turn allows us to compare Twitter users who answered the surveys with all those we contacted not just in terms of Twitter behavior, but also in terms of socio-demographic and political characteristics, and therefore evaluate whether the former is representative of the latter. As those invited to take the surveys were selected randomly, this process should allow us to ensure that our samples are representative of Germans and Italians who tweeted about the elections and, to the extent that they are not, to reweight the data accordingly.

As shown in Appendix C, respondents who provided their Twitter usernames were similar to those who answered the survey but did not provide their usernames in terms of demographic characteristics, interest in politics, and ideology. When compared with all the users we asked to participate in the survey, survey respondents turned out to follow more politicians' accounts and to have posted more tweets about the election, although there was no difference in terms of the popularity of different keywords posted by the two groups; in Germany, they were also more likely to be male.

To better ensure that our survey respondents are representative of the populations of Twitter users who tweeted about these elections, we weight our analyses by gender, region, number of political accounts followed, and number of tweets posted that mentioned any of our keywords. This approach is commonly adopted by survey researchers to ensure that sample margins match population margins in a set of key variables (Gellman & Hill, 2007, pp. 310-319). For those respondents who did not provide their Twitter usernames, we imputed five sets of values for the latter two variables using a Markov Chain Monte Carlo method (Gellman & Hill, 2007). We then computed five different sets of weights and ran multiple analyses using each of them, the results of which were then aggregated. Because we only weighted those cases for which we had information concerning all four variables, the total number of cases in our analyses is 999 for Germany and 1,408 for Italy. Therefore, while we do not argue that our samples are representative of the German and Italian populations as a whole, we do feel confident—when using the weighted analyses—that they are fairly representative of Germans and Italians who talked about the 2013 elections on Twitter, at least in so far as their online political activity, gender, and region is concerned.

Appendix C. Characteristics of Twitter Users Invited to Take the Survey, of Twitter Users Who Participated in the Survey and Provided Their Twitter Account Names, and of Twitter Users Who Participated in the Survey and Did Not Provide Their Twitter Account Names.

Socio-political characteristics	Germany			Italy		
	Did not give username	Gave username	<i>p</i>	Did not give username	Gave username	<i>p</i>
Percentage female	30.5	22.2	.003	40.5	37.3	.210
Average age (years)	34.9	35.1	.841	32.0	32.0	.942
Average educational level (0-1)	.65	.62	.010	.64	.62	.077
Average income bracket (0-1)	.49	.46	.073	.46	.45	.359
Average interest in politics (0-1)	.80	.82	.082	.75	.79	<.001
Ideology (left-right, 0-1)	.32	.33	.537	.38	.37	.803
Total	665	478		880	613	
Twitter activities	Invited to survey			Invited to survey		
	Invited to survey	Gave username	<i>p</i>	Invited to survey	Gave username	<i>p</i>
Percentage female (estimated)	51.7	38.4	<.001	38.2	38.3	.992
Number of followers	865	651	.069	236	239	.883
Total number of tweets	8,695	7,291	.053	3,223	2,983	.574
Tweets mentioning political keywords	6.86	25.04	<.001	12	31	<.001
Number of days since account created	672	930	<.001	605	781	<.001
Number of political accounts followed	5.95	17.49	<.001	11	20	<.001
Ideology (left-right, -3 to +3) ^a	-0.01	-0.03	0.239	-0.31	-0.44	0.022
Total	42,647	393		55,245	585	

^aIdeology was estimated based on the method described in Barberá (2015).

Appendix D. Dependent Variable(s): Types of Political Networks Respondents Engage With on Social Media (Respondents Engaging in Neutral Networks Excluded From Analysis).

	Germany			Italy		
	Supportive	Oppositional	Mixed	Supportive	Oppositional	Mixed
Face-to-face political networks (ref. mixed)						
Supportive	1.457**	-1.085	-1.191*	1.556***	-0.809*	-1.568***
Oppositional	-0.124	0.707	-0.745	0.169	0.988**	-1.931***
Ratio of political messages on the total exchanged on social media	0.115	-0.242*	0.130	0.068	-0.173**	0.162
Preferred use of social media	1.751*	-2.095*	-0.576	1.852***	-1.806**	-0.841
Source of political information						
Internet	0.399	0.480	-1.170	0.568	-0.308	-0.707
Newspapers	-0.796	1.078	0.116	-0.567	1.088*	-0.682
Radio	-1.153*	1.521*	-0.056	-0.327	-0.027	0.826
Television	-0.599	0.129	0.667	-0.354	-0.054	0.880
Political efficacy (disagreement with following sentences)						
“People don’t have any say”	0.570	-0.106	-0.924	-0.425	0.420	0.231
“Public officials don’t care”	-0.424	-0.296	1.271	0.864*	-0.505	-0.929
“Politics is too complicated”	-0.216	-0.504	1.222	0.089	-0.146	0.073
Interest in politics	-1.482	1.916	-0.183	-1.073	0.563	1.378
Trust in political parties	-0.016	-1.181	1.275	0.280	-0.041	-0.523
Offline political discussion	0.793	-0.641	-0.629	1.158	-0.604	-1.478
Gender (male)	0.104	-0.539	0.508	-0.098	0.027	0.149
Age	0.289	-0.429	-0.381	0.277	0.423	-1.518
Education	-0.851	1.107	0.065	0.080	-0.689	1.111
Income	-1.230	1.165	0.977	-0.525	0.654	-0.099
Constant	1.656	-2.381*	-2.654*	-0.715	-0.308	-1.556
N	322	322	322	560	560	560
Nagelkerke R ²	.291	.327	.176	.250	.281	.159
Log-likelihood	328.511	247.812	211.579	618.599	522.760	348.143

Note. Cell entries are log odds. Dummy variable identifying missing observations for income omitted from table. All variables range from 0 to 1 apart from political messages exchanged (0-10) and preferred use of social media (-1 to 1).

*** $p \leq .001$. ** $p \leq .01$. * $p \leq .05$.

Appendix E. German Respondents—Dependent Variable: Engagement With Supportive Political Networks on Social Media.

	B	SE	p	exp(B)	95% CI for exp(B)		99% CI for exp(B)	
					min	max	min	max
Face-to-face political networks (ref. neutral)								
Supportive	0.818	0.241	.002	2.265	1.390	3.692	1.178	4.357
Oppositional	−0.381	0.306	.217	0.683	0.371	1.258	0.304	1.537
Mixed	−0.365	0.372	.328	0.694	0.332	1.449	0.262	1.837
Ratio of political messages on the total exchanged on social media	0.153	0.042	.000	1.165	1.073	1.266	1.045	1.299
Preferred use of social media	1.240	0.436	.006	3.455	1.447	8.254	1.087	10.983
Source of political information								
Internet	0.078	0.441	.859	1.082	0.455	2.573	0.346	3.385
Newspapers	−0.460	0.330	.164	0.631	0.330	1.207	0.269	1.481
Radio	−1.046	0.284	.000	0.351	0.201	0.613	0.169	0.731
Television	−.406	0.332	.223	0.666	0.345	1.286	0.279	1.590
Political efficacy (disagreement with following sentences)								
“People don’t have any say”	0.108	0.476	.823	1.114	0.413	3.003	0.289	4.301
“Public officials don’t care”	0.167	0.437	.704	1.181	0.494	2.824	0.371	3.760
“Politics is too complicated”	−0.660	0.348	.058	0.517	0.261	1.024	.211	1.270
Interest in politics	1.601	0.538	.003	4.958	1.722	14.277	1.232	19.948
Trust in political parties	−0.276	0.504	.587	0.759	0.274	2.104	0.194	2.971
Offline political discussion	0.079	0.396	.841	1.083	0.495	2.366	0.386	3.039
Gender (male)	−0.128	0.208	.541	0.880	0.583	1.328	0.511	1.516
Age	−0.712	0.553	.200	0.491	0.165	1.464	0.116	2.079
Education	−0.431	0.503	.393	0.650	0.239	1.765	0.173	2.444
Income	−0.582	0.437	.183	0.559	0.237	1.315	0.181	1.721
Constant	−0.667	0.523	.202	0.513	0.184	1.429	0.133	1.973
N	727							
Nagelkerke R^2	.241							
Log-likelihood	834.045							
Percentage correctly predicted	69.9							

Note. Dummy variable identifying missing observations for income omitted from table. All variables range from 0 to 1 apart from political messages exchanged (0–10) and preferred use of social media (−1 to 1).

Appendix F. German Respondents—Dependent Variable: Engagement With Oppositional Political Networks on Social Media.

	B	SE	p	exp(B)	95% CI for exp(B)		99% CI for exp(B)	
					min	max	min	Max
Face-to-face political networks (ref. neutral)								
Supportive	−0.201	0.343	.561	0.818	0.413	1.622	0.330	2.029
Oppositional	0.899	0.350	.012	2.458	1.227	4.924	0.979	6.170
Mixed	0.489	0.492	.322	1.630	0.615	4.321	0.449	5.921
Ratio of political messages on the total exchanged on social media	−0.041	0.062	.509	0.960	0.849	1.085	0.816	1.128
Preferred use of social media	−1.032	0.578	.078	0.356	0.113	1.127	0.077	1.640
Source of political information								
Internet	1.023	0.651	.117	2.782	0.774	10.000	0.516	14.991
Newspapers	0.360	0.429	.401	1.434	0.619	3.322	0.475	4.327
Radio	0.612	0.436	.165	1.844	0.773	4.403	0.580	5.860
Television	−0.264	0.464	.571	0.768	0.305	1.934	0.226	2.614
Political efficacy (disagreement with following sentences)								
“People don’t have any say”	−0.201	0.556	.718	0.818	0.273	2.450	0.192	3.477
“Public officials don’t care”	−0.375	0.618	.546	0.688	0.200	2.359	0.134	3.536
“Politics is too complicated”	−0.039	0.521	.940	0.962	0.338	2.734	0.239	3.866
Interest in politics	−0.923	0.923	.331	0.398	0.057	2.770	0.028	5.697
Trust in political parties	−0.641	0.749	.399	0.527	0.114	2.437	0.067	4.154
Offline political discussion	0.661	0.560	.239	1.937	0.641	5.853	0.450	8.336
Gender (male)	−0.227	0.298	.449	0.797	0.440	1.444	0.362	1.755
Age	−1.051	0.992	.303	0.350	0.044	2.792	0.020	5.987
Education	1.025	0.714	.156	2.787	0.670	11.599	0.419	18.522
Income	1.421	0.797	.086	4.141	0.804	21.324	0.452	37.950
Constant	−3.087	0.945	.003	0.046	0.007	0.317	0.003	0.625
N	727							
Nagelkerke R ²	.125							
Log-likelihood	518.951							
Percentage correctly predicted	86.5							

Note. Dummy variable identifying missing observations for income omitted from table. All variables range from 0 to 1 apart from political messages exchanged (0–10) and preferred use of social media (−1 to 1).

Appendix G. German Respondents—Dependent Variable: Engagement With Mixed Political Networks on Social Media.

	B	SE	p	exp(B)	95% CI for exp(B)		99% CI for exp(B)	
					min	max	min	max
Face-to-face political networks (ref. neutral)								
Supportive	0.832	0.554	.140	2.297	0.755	6.988	0.521	10.127
Oppositional	1.200	0.553	.031	3.320	1.115	9.879	0.788	13.986
Mixed	1.696	0.615	.007	5.452	1.606	18.513	1.080	27.531
Ratio of political messages on the total exchanged on social media	0.149	0.095	.126	1.160	0.957	1.406	0.898	1.500
Preferred use of social media	0.224	0.777	.775	1.251	0.260	6.021	0.153	10.246
Source of political information								
Internet	−0.386	0.845	.648	0.680	0.130	3.568	0.077	6.016
Newspapers	−0.167	0.602	.782	0.846	0.259	2.764	0.178	4.021
Radio	0.562	0.589	.343	1.755	0.542	5.685	0.368	8.364
Television	−0.008	0.658	.990	0.992	0.263	3.748	0.167	5.876
Political efficacy (disagreement with following sentences)								
“People don’t have any say”	−0.581	0.767	.450	0.559	0.122	2.554	0.075	4.168
“Public officials don’t care”	0.849	0.799	.290	2.338	0.480	11.385	0.288	18.959
“Politics is too complicated”	0.799	0.740	.285	2.223	0.506	9.756	0.311	15.876
Interest in politics	0.846	1.167	.469	2.331	0.235	23.107	0.114	47.729
Trust in political parties	0.597	0.912	.517	1.817	0.283	11.667	0.149	22.162
Offline political discussion	−0.118	0.800	.883	0.889	0.184	4.304	0.111	7.113
Gender (male)	0.367	0.458	.427	1.444	0.575	3.626	0.422	4.936
Age	−0.401	1.050	.703	0.670	0.083	5.431	0.042	10.784
Education	−1.042	0.905	.252	0.353	0.059	2.124	0.033	3.792
Income	0.812	0.895	.366	2.253	0.382	13.292	0.215	23.578
Constant	−5.569	1.221	.000	0.004	0.000	0.043	0.000	0.093
N	727							
Nagelkerke R^2	.141							
Log-likelihood	312.860							
Percentage correctly predicted	93.4							

Note. Dummy variable identifying missing observations for income omitted from table. All variables range from 0 to 1 apart from political messages exchanged (0–10) and preferred use of social media (−1 to 1).

Appendix H. Italian Respondents—Dependent Variable: Engagement With Supportive Political Networks on Social Media.

	B	SE	p	exp(B)	95% CI for exp(B)		99% CI for exp(B)	
					min	max	Min	max
Face-to-face political networks (ref. neutral)								
Supportive	0.998	0.167	.000	2.714	1.956	3.766	1.764	4.175
Oppositional	0.040	0.192	.836	1.040	0.713	1.517	0.633	1.710
Mixed	0.032	0.271	.905	1.033	0.607	1.757	0.513	2.078
Ratio of political messages on the total exchanged on social media	0.120	0.038	.003	1.128	1.044	1.217	1.019	1.248
Preferred use of social media	1.714	0.355	.000	5.550	2.763	11.147	2.217	13.893
Source of political information								
Internet	0.171	0.417	.682	1.187	0.519	2.716	0.397	3.550
Newspapers	−0.690	0.278	.014	0.501	0.289	0.868	0.243	1.036
Radio	−0.508	0.230	.028	0.601	0.382	0.946	0.331	1.092
Television	0.078	0.258	.762	1.081	0.652	1.792	0.557	2.100
Political efficacy (disagreement with following sentences)								
“People don’t have any say”	0.042	0.231	.855	1.043	.663	1.640	0.575	1.890
“Public officials don’t care”	0.338	0.262	.197	1.402	0.839	2.343	0.714	2.753
“Politics is too complicated”	−0.098	0.202	.626	0.906	0.610	1.346	0.539	1.524
Interest in politics	−0.141	0.458	.759	0.868	0.347	2.170	0.257	2.934
Trust in political parties	0.379	0.301	.209	1.461	0.808	2.639	0.671	3.180
Offline political discussion	0.257	0.536	.632	1.293	0.452	3.696	0.325	5.142
Gender (male)	−0.211	0.149	.158	0.810	0.605	1.085	0.551	1.190
Age	−0.561	0.438	.201	0.570	0.240	1.353	0.183	1.782
Education	0.361	0.492	.463	1.435	0.546	3.773	0.402	5.123
Income	−0.094	0.314	.766	0.910	0.485	1.708	0.394	2.104
Constant	−1.348	0.506	.008	0.260	0.096	0.700	0.071	0.955
N	1,167							
Nagelkerke R ²	.164							
Log-likelihood	1,391.319							
Percentage correctly predicted	68.7							

Note. Dummy variable identifying missing observations for income omitted from table. All variables range from 0 to 1 apart from political messages exchanged (0-10) and preferred use of social media (−1 to 1).

Appendix I. Italian Respondents—Dependent Variable: Engagement With Oppositional Political Networks on Social Media.

	<i>B</i>	<i>SE</i>	<i>p</i>	<i>exp(B)</i>	95% CI for <i>exp(B)</i>		99% CI for <i>exp(B)</i>	
					min	max	Min	max
Face-to-face political networks (ref. neutral)								
Supportive	0.183	0.296	.538	1.201	0.668	2.157	0.554	2.604
Oppositional	1.756	0.251	.000	5.788	3.532	9.485	3.020	11.094
Mixed	1.082	0.348	.002	2.950	1.489	5.846	1.200	7.254
Ratio of political messages on the total exchanged on social media	−0.058	0.046	.211	0.944	0.862	1.033	0.838	1.063
Preferred use of social media	−1.056	0.462	.022	0.348	0.141	0.861	0.106	1.146
Source of political information								
Internet	−0.488	0.509	.339	0.614	0.225	1.675	0.163	2.307
Newspapers	0.060	0.369	.872	1.062	0.512	2.200	0.406	2.779
Radio	0.005	0.308	.987	1.005	0.549	1.839	0.454	2.227
Television	−0.068	0.359	.850	0.934	0.460	1.897	0.367	2.376
Political efficacy (disagreement with following sentences)								
“People don’t have any say”	0.469	0.311	.132	1.598	0.868	2.942	0.716	3.568
“Public officials don’t care”	−0.239	0.395	.546	0.787	0.360	1.723	0.279	2.219
“Politics is too complicated”	0.000	0.266	1.000	1.000	0.594	1.683	0.504	1.982
Interest in politics	0.805	0.556	.148	2.238	0.751	6.671	0.531	9.422
Trust in political parties	−0.386	0.412	.349	0.680	0.303	1.526	0.235	1.970
Offline political discussion	−1.014	0.692	.144	0.363	0.093	1.413	0.061	2.170
Gender (male)	0.041	0.201	.838	1.042	0.703	1.546	0.621	1.750
Age	−0.347	0.552	.530	0.707	0.239	2.086	0.170	2.931
Education	0.290	0.617	.639	1.336	0.398	4.480	0.272	6.552
Income	0.227	0.368	.537	1.255	0.610	2.586	0.485	3.247
Constant	−1.893	0.660	.004	0.151	0.041	0.549	0.027	0.825
<i>N</i>	1,167							
Nagelkerke <i>R</i> ²	.157							
Log-likelihood	889.100							
Percentage correctly predicted	85.1							

Note. Dummy variable identifying missing observations for income omitted from table. All variables range from 0 to 1 apart from political messages exchanged (0–10) and preferred use of social media (−1 to 1).

Appendix J. Italian Respondents—Dependent Variable: Engagement With Mixed Political Networks on Social Media.

	B	SE	p	exp(B)	95% CI for exp(B)		99% CI for exp(B)	
					min	max	Min	max
Face-to-face political networks (ref. neutral)								
Supportive	0.580	0.391	.140	1.786	0.825	3.866	0.644	4.950
Oppositional	0.228	0.404	.572	1.256	0.569	2.775	0.443	3.562
Mixed	2.072	0.446	.000	7.942	3.274	19.268	2.456	25.690
Ratio of political messages on the total exchanged on social media	0.126	0.066	.055	1.135	0.997	1.291	0.957	1.345
Preferred use of social media	−0.675	0.680	.322	0.509	0.134	1.940	0.088	2.965
Source of political information								
Internet	−0.983	0.748	.189	0.374	0.086	1.621	0.054	2.570
Newspapers	−0.433	0.521	.408	0.648	0.231	1.823	0.165	2.545
Radio	0.815	0.449	.070	2.259	0.936	5.452	0.709	7.194
Television	0.911	0.578	.117	2.487	0.793	7.794	0.550	11.249
Political efficacy (disagreement with following sentences)								
“People don’t have any say”	−0.048	0.427	.911	0.953	0.412	2.204	0.317	2.868
“Public officials don’t care”	−0.886	0.543	.103	0.412	0.142	1.198	0.101	1.678
“Politics is too complicated”	0.311	0.393	.429	1.365	0.631	2.952	0.495	3.766
Interest in politics	1.969	1.059	.074	7.164	0.811	63.246	0.376	136.337
Trust in political parties	−0.768	0.605	.205	0.464	0.142	1.521	0.097	2.212
Offline political discussion	−0.587	1.384	.675	0.556	0.033	9.400	0.012	25.078
Gender (male)	0.212	0.287	.460	1.236	0.705	2.168	0.590	2.588
Age	−0.798	0.833	.340	0.450	0.087	2.334	0.051	3.957
Education	0.614	0.964	.525	1.848	0.275	12.431	0.149	22.930
Income	−0.528	0.571	.357	0.590	0.190	1.827	0.132	2.633
Constant	−4.822	1.210	.000	0.008	0.001	0.089	0.000	0.195
N	1,167							
Nagelkerke R ²	.143							
Log-likelihood	503.732							
Percentage correctly predicted	93.4							

Note. Dummy variable identifying missing observations for income omitted from table. All variables range from 0 to 1 apart from political messages exchanged (0-10) and preferred use of social media (−1 to 1).

Appendix K. Question Wording, Response Modes, and Descriptive Statistics for All Control Variables Included in the Models.

Question wording	Response modes	Variable ^a
Overall, how important are social media to you personally when it comes to finding other people who share your views about important political issues?	Very important, somehow important, not too important, not at all important, (don't know)	"Preferred use of social media" ^b Italian data set $M = .017, SD = .201$ German data set $M = .039, SD = .240$
Overall, how important are social media to you personally when it comes to finding other people who do not share your views about important political issues?	Very important, somehow important, not too important, not at all important, (don't know)	
Generally speaking, how much are you interested in politics?	Very interested, moderately interested, slightly interested, not interested at all, (don't know)	"Interest in politics" Italian data set $M = .773, SD = .227$ German data set $M = .791, SD = .242$
To what extent do you agree or disagree with each of these statements? People like me don't have any say about what the government does.	Definitely not true, not really true, quite true, definitely true, (don't know)	"People don't have any say" (disagreement with) Italian data set $M = .483, SD = .316$ German data set $M = .540, SD = .279$
To what extent do you agree or disagree with each of these statements? Public officials care what people like me think.	Definitely not true, not really true, quite true, definitely true, (don't know)	"Public officials don't care" (disagreement with) Italian data set $M = .341, SD = .288$ German data set $M = .416, SD = .268$
To what extent do you agree or disagree with each of these statements? Sometimes, politics and government seem so complicated that a person like me can't really understand what's going on,	Definitely not true, not really true, quite true, definitely true, (don't know)	"Politics is too complicated" (disagreement with) Italian data set $M = .536, SD = .346$ German data set $M = .622, SD = .297$
How much do you trust the following institutions and organizations? Political parties.	A lot, a fair amount, a little, not at all, (don't know)	"Trust in political parties" Italian data set $M = .242, SD = .255$ German data set $M = .386, SD = .246$
How often do you talk about politics with your friends, family, and acquaintances?	Every day or almost every day, a few times a week, a few times a month, never or almost never, (don't know)	"Offline political discussion (frequency)" Italian data set $M = .880, SD = .179$ German data set $M = .657, SD = .316$
How often do you turn to each of the following media outlets for getting political news of your interest? Internet.	Never, at least once a month, at least once a week, every day, more than once per day, (don't know)	"Source of political information: Internet" Italian data set $M = .843, SD = .210$ German data set $M = .789, SD = .275$
How often do you turn to each of the following media outlets for getting political news of your interest? Newspapers.	Never, at least once a month, at least once a week, every day, more than once per day, (don't know)	"Source of political information: Newspapers" Italian data set $M = .410, SD = .295$ German data set $M = .338, SD = .307$
How often do you turn to each of the following media outlets for getting political news of your interest? Radio.	Never, at least once a month, at least once a week, every day, more than once per day, (don't know)	"Source of political information: Radio" Italian data set $M = .528, SD = .325$ German data set $M = .496, SD = .357$

Appendix K. (Continued)

Question wording	Response modes	Variable ^a
How often do you turn to each of the following media outlets for getting political news of your interest? Television.	Never, at least once a month, at least once a week, every day, more than once per day, (don't know)	"Source of political information: Television" Italian data set $M = .633, SD = .278$ German data set $M = .488, SD = .328$
Are you . . .	Male, female	"Gender (male)" Italian data set Male 56,6% of respondents German data set Male 65,4% of respondents
What year were you born in? [Italian data set]	[Open answer] Italian data set	"Age" Italian data set
How old are you? [German data set]	(Youngest resp. aged 13, oldest 76) German data set (Youngest resp. aged 13, oldest 72)	$M = .308, SD = .182$ German data set $M = .351, SD = .207$
What best describes your final level of education?	None, primary school, secondary school degree, vocational school degree, high school degree, undergraduate degree, postgraduate degree, doctoral degree [Italian data set] None, primary school, secondary school (Hauptschule), high school (Abitur), undergraduate degree, postgraduate degree, doctoral degree [German data set]	"Education" Italian data set $M = .636, SD = .153$ German data set $M = .622, SD = .214$
What is the gross annual income, before tax or other deductions, for you and your family? [Italian data set]	Less than 6,000 euro; between 6,000 and 12,000 euro; between 12,000 and 18,000 euro; between 18,000 and 24,000 euro; between 24,000 and 30,000 euro; between 30,000 and 36,000 euro; between 36,000 and 42,000 euro; between 42,000 and 50,000 euro; between 50,000 and 75,000 euro; more than 100,000 euro. [Italian data set]	"Income" ^c Italian data set $M = .463, SD = .250$ German data set $M = .455, SD = .231$
What is the gross monthly income, before tax or other deductions, for you and your family? [German data set]	Less than 500 euro; between 500 and 900 euro; between 900 and 1,300 euro; between 1,300 and 1,500 euro; between 1,500 and 2,000 euro; between 2,000 and 2,600 euro; between 2,600 and 3,500 euro; between 3,500 and 4,500 euro; between 4,500 and 6,000 euro; between 6,000 and 8,000 euro; more than 8,000 euro [German data set]	

^aAll control variables included in our models range from 0 to 1 apart from preferred use of social media (−1 to 1). Descriptive statistics presented in the table refer to these variables (weighted as described in Appendix B).

^bThis variable was built based on responses to the two questions, which we combined by subtracting the values of the second from those of the first, so that respondents who claimed that agreement was more important than disagreement would have positive values, whereas those who stated that disagreement was more important than agreement would have negative values, and those who attributed equal importance to agreement and disagreement would have a score of zero.

^cBecause our income variable included a large proportion of missing data we mean-replaced these missing values and added a dummy variable to the analysis to identify these cases (further explanations of the method and implications are in Note 18 in the article).

Appendix L. Dependent Variable(s): Types of Political Networks Respondents Engage With on Social Media (Variable Measuring Preference for Encountering Agreeing vs. Disagreeing Viewpoints on Social Media Excluded From Models).

	Germany			Italy		
	Supportive	Oppositional	Mixed	Supportive	Oppositional	Mixed
Face-to-face political networks (ref. Neutral)						
Supportive	0.890*** (0.223)	-0.262 (0.351)	0.831 (0.545)	1.040*** (0.165)	0.198 (0.292)	0.681 (0.384)
Oppositional	-0.355 (0.283)	1.027*** (0.312)	1.286* (0.563)	0.087 (0.193)	1.751*** (0.247)	0.243 (0.404)
Mixed	-0.280 (0.368)	0.392 (0.526)	1.720** (0.607)	0.079 (0.266)	1.075** (0.345)	2.094*** (0.438)
Ratio of political messages on the total exchanged on social media	0.133** (0.042)	-0.038 (0.064)	0.168 (0.095)	0.131*** (0.037)	-0.064 (0.045)	0.097 (0.065)
Source of political information						
Internet	0.126 (0.449)	0.837 (0.598)	-0.311 (0.826)	0.152 (0.408)	-0.480 (0.504)	-0.882 (0.739)
Newspapers	-0.522 (0.310)	0.297 (0.419)	-0.039 (0.589)	-0.728** (0.267)	0.049 (0.355)	-0.438 (0.503)
Radio	-0.829** (0.273)	0.549 (0.428)	0.477 (0.565)	-0.534* (0.221)	-0.006 (0.302)	0.714 (0.435)
Television	-0.391 (0.303)	-0.216 (0.458)	0.088 (0.656)	0.117 (0.253)	-0.014 (0.351)	0.854 (0.567)
Political efficacy (disagreement with following sentences)						
"People don't have any say"	0.185 (0.426)	-0.148 (0.546)	-0.430 (0.728)	0.079 (0.228)	0.441 (0.308)	-0.164 (0.421)
"Public officials don't care"	-0.130 (0.415)	-0.134 (0.608)	0.748 (0.773)	0.340 (0.258)	-0.236 (0.393)	-0.852 (0.531)
"Politics is too complicated"	-0.456 (0.329)	-0.001 (0.503)	0.842 (0.748)	-0.048 (0.197)	-0.005 (0.262)	0.264 (0.379)
Interest in politics	1.412** (0.502)	-0.644 (0.831)	0.784 (1.105)	-0.288 (0.444)	0.912 (0.551)	2.272* (1.058)
Trust in political parties	0.084 (0.494)	-0.955 (0.721)	0.534 (0.863)	0.451 (0.298)	-0.445 (0.405)	-0.601 (0.585)
Offline political discussion	-0.002 (0.368)	0.758 (0.515)	-0.112 (0.777)	0.421 (0.526)	-1.095 (0.675)	-0.523 (1.359)
Gender (male)	-0.105 (0.202)	-0.143 (0.289)	0.378 (0.460)	-0.203 (0.146)	0.029 (0.199)	0.216 (0.282)
Age	-0.674 (0.533)	-0.925 (0.891)	-0.388 (1.017)	-0.487 (0.427)	-0.381 (0.548)	-0.890 (0.815)
Education	-0.434 (0.495)	0.838 (0.685)	-1.089 (0.896)	0.377 (0.486)	0.129 (0.613)	0.555 (0.941)
Income	-0.558 (0.422)	1.159 (0.746)	0.822 (0.849)	-0.094 (0.307)	0.241 (0.359)	-0.381 (0.552)
Constant	-0.673 (0.478)	-3.179*** (0.879)	-5.799*** (1.166)	-1.512** (0.499)	-1.776** (0.646)	-4.948*** (1.194)
N	776	776	776	1,193	1,193	1,193
Nagelkerke R ²	.205	.113	.145	.137	.148	.138
Log-likelihood	914.299	549.283	323.175	1,439.763	907.024	525.302

Note. Cell entries are log odds, SE in parentheses. Dummy variable identifying missing observations for income omitted from table. All variables range from 0 to 1 apart from political messages exchanged (0-10).

*** $p \leq .001$. ** $p \leq .01$. * $p \leq .05$.

Appendix M. Bivariate Relationship Between Online and Offline Networks of Political Discussion, Germany.

		Offline networks				N
		Supportive	Mixed	Oppositional	Neutral	
Online networks	Supportive	56.4%	33.1%	32.9%	29.6%	369
	Mixed	6.8%	15.8%	8.8%	3%	60
	Oppositional	8.3%	13%	23.8%	11.6%	114
	Neutral	28.5%	38.1%	34.5%	55.8%	366
	N	345	79	154	331	909

Appendix N. Bivariate Relationship Between Online and Offline Networks of Political Discussion, Italy.

		Offline networks				N
		Supportive	Mixed	Oppositional	Neutral	
Online networks	Supportive	52.4%	29%	27.9%	25.5%	478
	Mixed	7.4%	20.9%	6.1%	4.3%	97
	Oppositional	9.1%	19.7%	32.1%	8%	207
	Neutral	31.1%	30.4%	33.9%	62.2%	556
	N	465	112	340	421	1,338