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Social Bots in Election Campaigns: Theoretical, Empirical, and Methodological Implications

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Social bots mimic and potentially manipulate humans and their behaviours in social networks. The public sphere might be especially vulnerable to their impacts, which is why we first discuss their potential influence on the public sphere from a theoretical perspective. From an empirical perspective, we analyzed Twitter followers of seven German parties before (N = 638,674) and during (N = 838,026) the 2017 electoral campaigns regarding bot prevalence and activities. The results revealed that the share of social bots increased from 7.1% before to 9.9% during the election campaigns. The percentage of active social bots remained roughly the same. An analysis of the content distributed by both the most popular and the most active bots showed that they disseminate few political hashtags, and that almost none referred to German politics. We discuss the results against the background of normative traditions of public sphere theories and address the methodological challenges bots pose in political communication.

Keywords social bots, elections, Twitter, public sphere, Germany

Social bots are computer programs that mimic and potentially manipulate humans and their behaviors in social networks (Ferrara, Varol, Davis, Menczer, & Flammini, 2016; Wagner, Mitter, Körner, & Strohmaier, 2012). Bots post in online forums and dating platforms, and like, comment on, and share social media contributions. They are cheap tools to make content, topics, or actors appear more popular than they really are. They start and catalyze online phenomena to stir outrage and artificial hypes, while neither people nor trending algorithms can discern them with full accuracy as non-human agents. Social bots differ from more general bot software that delivers simple services around information retrieval, selection, or the creation of personalized preferences without directly interacting with Internet users (Woolley, 2016).

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Social bots are no longer a marginal phenomenon on social media platforms. On Twitter, 9% to 15% of users are estimated to be bots (Varol, Ferrara, Davis, Menczer, & Flammini, 2017). There has been an exponential growth in the number of Twitter bots on the largest open-source online code repository, GitHub—which enables people with few programming skills to deploy social bots for their (political) purposes (Kollanyi, 2016). Their everyday occurrence makes analysis and reflection imperative from a social science perspective, and calls for a convergence of social and computational science approaches. How do social bots influence and change social and political discourses that are invisible and indiscernible to Internet users? Do social bots endanger and challenge the interactive and participatory potential of digital communication in mass democracies? How should studies assess empirical evidence of social bots' prevalence, activities, and impacts, and what does this mean for studies on political communication in social media generally?

From the perspective of political communication, we address social bots from three angles: theoretical, empirical, and methodological. We begin with a review of the theory and current literature regarding social bots, to discuss how they work and why they may create problems for democratic processes and public communication, drawing on public sphere theories. We then present an empirical study of social bots among Twitter followers of Germany's political parties before and during the country's 2017 national election campaigns. From a methodological perspective, this article raises the question of how political communication scholars who work with social media data should deal with social bots.

Theory: Social Bots, Agency, and Normative Models of the Public Sphere

From a theoretical perspective, social bots challenge many concepts that social scientists take for granted—for instance, the question of what constitutes an *actor*. While some authors understand bots as "automated social actors" (Abokhodair, Yoo, & McDonald, 2015, p. 2), the question of technology and non-human agency is theoretically more complex. Technologies designed and programmed by humans embody social values and business models; they are encoded with human intentions and have limited agency of their own (Klinger & Svensson, 2018). Their behavior is human-like and human-guided, which makes them human-dependent rather than autonomous actors. For instance, people overcome their physical limitations by using bots to retweet messages under multiple personas. Social bots impact communal relationship types (*Vergemeinschaftung*)—that is, social relationships based on a sense of belonging together—as well as associative relationships (*Vergesellschaftung*)—that is, social relationships based on rational agreements (Weber, 1922, p. §9). How do we account for social structures and relations that include social machines? And, since we know that social bots generate a large percentage of Internet traffic (Zeifman, 2015) and interact with human users, what does this mean for the formation of social relations and society, especially the public sphere?

On the one hand, there are many useful tasks for social bots in political communication. Similar to bots helping people to choose new outfits, bots could help citizens identify their political preferences and match them with parties and candidates (e.g., in voting advice applications, such as Wahl-O-Mat in Germany or smartvote in Switzerland). On the other hand, problems start when bots operate in disguise, interacting with citizens, voters, and stakeholders without people knowing. Social bots can orchestrate campaigns to hype organizations, alter perceptions of political reality by spreading propaganda (Abokhodair et al., 2015; Boshmaf, Muslukhov, Beznosov, & Ripeanu, 2011), disrupt government and organizational communication (Woolley & Howard, 2016a), feign grassroots movements (Rathnayake & Buente, 2017), spread misinformation (Shao et al., 2018), and alter public opinion by simulating the popularity of or protest against topics or actors (Ferrara et al., 2016). This implies that an increasing amount of online communication is non-authentic, but at the same time intended to yield real consequences.

Social bots can have different functions based on the behaviors they are programmed for. They can be merely *passive*, connecting with a number of accounts in order to boost the number of followers and their interconnectedness without contributing content. In this way, they make actors appear more popular and socially acceptable than they really are, encouraging others to follow or "like" them (the so-called bandwagon effect; Sundar, Oeldorf-Hirsch, & Xu, 2008). Alternatively, they could be *active*, liking, sharing, retweeting, commenting and broadcasting information, interacting in debates, and fueling discussions.

Online public spheres, such as social media platforms and online forums, have become commonplace for deliberation, political talk, discourse, and the articulation and aggregation of political interests. Whether or not participants realize it, their interactions are likely to be infiltrated by social bots and their agendas; as Mitter, Wagner, and Strohmaier (2013, p. 1) put it: "Without a deep understanding of the impact of such attacks, the potential of online social networks as an instrument for facilitating discourse or democratic processes is in jeopardy." However, whether social bots pose a threat to democracy and lead to disrupted public spheres (Bennett & Pfetsch, 2018), largely depends on the normative perspective. Table 1 describes Ferree, Gamson, Gerhards, & Rucht's (2002) four models of the public sphere in modern democracies: representative-liberal, participatory-liberal, discursive, and constructionist.

In a representative-liberal tradition, the public sphere is an elite-dominated, free, and transparent forum that enables citizens to repeatedly choose (and replace) their

Table 1
Normative traditions of public spheres

	Inclusion	Processes	Key Bot Problems
Representative-liberal	Elites, experts	Recurring exchange of political elites in elections	Quantitative misrepresentation of popularity
Participatory-liberal	Popular inclusion	Plural decision making	Diffusion of fake political interests (astroturfing)
Discursive	Popular inclusion	Deliberation	Non-authentic, manufactured participants; lack of mutual respect and rationality
Constructionist	Popular inclusion	Empowerment of marginalized actors, expansion of political community	Non-authentic, manufactured participants

Note. Overview of the models of public sphere is based on Ferree and colleagues (2002, p. 316).

representatives. In this instance, bots potentially disturb the key principles of proportionality and transparency. By discreetly making some ideas and actors appear more popular than they really are, coverage of political actors becomes disproportional to their de facto citizen following. Although citizens may be unaware of the situation, it becomes impossible for them to take popularity cues (Keller & Kleinen-von Königslöw, 2018; Porten-Cheé, Haßler, Jost, Eilders, & Marcus, 2017) from political actors in social networks as a proxy of public opinion and their popularity among fellow citizens, and there may even be a conflict of popularity cues online (likes, retweets) and offline (polls, media coverage). Thus, in a representative-liberal perspective, bots are a problem when they distort political competition, intervene in campaigns, and influence elections' outcomes. If bots boost political parties or candidates' number of Twitter followers, Facebook friends, or group members, they threaten the functioning of key democratic processes.

In a participatory-liberal tradition, the public sphere is a space for public discourse that seeks to achieve maximum popular inclusion—not only during election campaigns, but all the time. Voices should not be linked to proportionality, but to plurality: all interests and actors in a community should be included and heard. However, with increasing bot presence, the desired inclusion of grassroots movements may turn more to *astroturfing*, "grassroots support that is artificial because it is manufactured and does not arise spontaneously" (Klotz, 2007, p. 5). The principle of plurality is based on the premise of authentic interests and stakes in a society. Bots may insert non-authentic interests (interests no human or group in a society has ever voiced) and manipulated interests (fake interests that are manufactured to distort plurality). It becomes impossible for a society to monitor itself when machines disguised as societal members enter and manipulate the marketplace of ideas. This means that bots are not only a problem because they lead to quantitative misrepresentations and make parties or candidates seem more popular than they are, but because they could potentially give voice to nonexistent ideas. In the functioning of public spheres, this is particularly relevant when bots send and multiply (retweet) political messages.

This aspect becomes even more toxic in the discursive tradition: "But when important normative questions are at stake, it is crucial that the discussion not be limited to actors at the centre of the political system. On such issues, a well-functioning public sphere should simultaneously include actors from the periphery as well[…]" (Ferree et al., 2002, p. 300). Habermas's distinction between autonomous (*autochtone*) and power-regulated (*vermachtete*) actors from the periphery becomes obsolete when automated, manipulative, and interest-driven bots enter a discourse. Bots have no intention to understand or consider others' opinions, and their participation in political discourse only emphasizes their creators' lack of respect for deliberative processes. The idea that decisions are made collectively, and conflicts are resolved based on an argument's quality rather than on the number of supporters for an argument, is irreconcilable with social bots. With bots, discourse becomes impossible; debate turns into a travesty.

Finally, a constructionist perspective on public spheres focuses not only on plurality and inclusion, but on difference and mutual recognition: "Recognition politics, sometimes called identity politics, creates a good public sphere by decentring dominant speakers and their assumptions of what is 'natural'" (Ferree et al., 2002, p. 308). In this tradition, everything is political, whether it takes place in private or in public, wherever power structures appear. The normative objective is to give voice to the marginalized, contesting and breaking "the boundaries between the public and private" (p. 311). This notion of public conversation and democratic processes is seen as particularly vulnerable to the participation of bots, because it seeks to empower previously silent voices and to include fringe groups and their political claims, and prefers narrative styles over rational, unemotional debate. Bots can boost popularity cues and take on the identity of an assumed marginalized group (Howard, Woolley, & Calo, 2018). Constructionist visions of public discourse depend on authentic individuals contributing genuine perspectives from their life-worlds (*Lebenswelt*), which are easily infiltrated and undermined by bots.

Bots are not inherently evil forces, and they are not all problematic for the same reasons. Any assessment of their impacts must acknowledge their empirical behavior patterns and a theoretical reflection on normative assumptions about political communication and the public sphere.

Literature Review: What We Know About Social Bots in Political Communication

While these questions are being discussed in blogs and newspapers, communication research is only starting to focus on social bots. Initial social science research projects have made it clear that social bots are by no means a merely technical phenomenon, but change how Internet users interact and form social relations among each other, and with institutions, organizations, and society. Social scientists have only recently begun to address their potential to intervene in election campaigns and to distort public communication and deliberation (Hegelich & Janetzko, 2016; Woolley, 2016).

Social bots exist to participate in human interaction and discourse, and are finding a fertile habitat in social media networks. Approximately one-quarter of Donald Trump's Twitter followers during the 2016 U.S. presidential campaign were bots (Woolley & Howard, 2016b). By focusing on hashtags, Kollanyi, Howard, and Woolley (2016) found that bots made up a large part of Twitter traffic during the campaign and privileged Trump messages over Clinton ones. Bessi and Ferrara (2016) found that social bots were present and did influence the U.S. presidential campaign: of all Twitter users involved, about 20% were bots. They also showed how easy it is to employ bots, even for inexperienced and non-tech-savvy users, since they are offered by diverse companies, sometimes even on a monthly subscription basis (p. 2). Bots intervened in the Brexit debate (Howard & Kollanyi, 2016), and the online petition for a second referendum on Brexit in June 2016 was "signed" by 77,000 bots (BBC, 2016). Bastos and Mercea (2017) discovered a network of 13,493 Twitter bots supporting the Leave EU campaign. Social bots drove the #MacronLeaks disinformation campaign: "the users who engaged with MacronLeaks are mostly foreigners with a pre-existing interest in alt-right topics and alternative news media, rather than French users with diverse political views. Concluding, anomalous account usage patterns suggest the possible existence of a black-market for reusable political disinformation bots" (Ferrara, 2017, p. 1). A study of Germany's 2017 election campaigns at the Oxford Internet Institute found that "highly automated" tweeting increased from 5.7% to 7.4% between February and September 2017. It also compared data from other projects but with the same research design, finding between 5.2% and 16.5% automated tweeting in various campaigns (Neudert, Kollanyi, & Howard, 2017). Previous studies outside the U.S. and European contexts found that right-wing parties and radical opposition parties used social bots more often than other parties (Schäfer, Evert, & Heinrich, 2017). Hegelich and Janetzko (2016) identified and analyzed a botnet connected to the Ukraine conflict and showed that social bots have political agendas and act relatively autonomously on the basis of complex algorithms.

This is all the more relevant because experimental studies show that users perceive social bots as equally credible, competent, attractive, and interactive as human agents (Edwards, Edwards, Spence, & Shelton, 2014; Everett, Nurse, & Erola, 2016). In this perspective, social bots can be understood as new actors in digital political communication and a key element of what has been termed *computational propaganda*: "We define computational propaganda as the assemblage of social media platforms, autonomous agents, and big data tasked with the manipulation of public opinion" (Woolley & Howard, 2016a, p. 4886).

From previous empirical studies on social bots, we can conclude that bots are omnipresent on platforms, particularly on Twitter, and that they are being used to influence political and other debates. This case study of how social bots interfere with the digital public sphere focuses on Germany's 2017 national elections seeks to answer five research questions.

Previous studies found that between 5% and 25% of Twitter accounts are bots (Bessi & Ferrara, 2016; Neudert et al., 2017; Varol et al., 2017) and that the number of bots is higher during a campaign phase than in a non-electoral period, especially since bots are sometimes removed from a platform after a campaign (Bastos & Mercea, 2017). Based on this, we ask the following questions:

RQ1: How many social bots follow Twitter accounts of German parties?

RQ2: Are there more social bots during the election campaign than in a non-electoral period?

While passive social bots among a party's followers may increase their popularity, active bots' functionalities are more sophisticated. They are able to like or retweet parties' messages, making them appear more popular and spreading them through the network. During election campaigns, the incentives to use bots to increase a party's visibility and to impact on political debate are higher, both for a party's supporters and other actors with an interest in influencing an election (Ferrara, 2017).

RQ3: Are there more active social bots during the election campaign than in the non-electoral period?

All but one political party in Germany have pledged to not strategically use social bots during their campaigns, after social bots became a topic of public debate. One party, the right-wing populist AfD (Alternative for Germany) declared in October 2016 that "of course" they would implement social bots in the election campaign—"after all, for young parties such as ours social media tools are important instruments to proliferate our positions among voters" (Stürzenhofecker, 2016, p. 1).[1] A few days later, the party retracted this statement with a declaration not to use bots in the campaign. However, since similar right-wing populist parties in Japan and France used bots (Ferrara, 2017; Schäfer et al., 2017), and Neudert et al. (2017) found that most bots were supporting AfD, we ask the following:

RQ4: Does the right-wing populist party AfD have the largest share of social bots among its followers?

Most studies measuring bots during election campaigns have remained silent on the content disseminated by bots (Zhang & Lu, 2016). Bots' presence alone is regarded as problematic. Nonetheless, it is possible that the same bots that boost parties and candidates' popularity levels spread no political messages, only commercial advertisements (Maireder, Weeks, Gil de Zúñiga, & Schlögl, 2016) or even nonsensical content (Bucher, 2017). We investigate whether bots post political content, and if they do it more often during an election period than in a non-electoral period.

RQ5: Do social bots disseminate political content, and if so, more during the election campaign than in the non-electoral period?

A final aspect in this literature review addresses the methodological approaches of bot-detection in studies. Bots avoid detection, and their creators invest effort into their resembling human users. Thus, it is not easy to identify bots and to distinguish these Twitter accounts from human accounts. Zhang and Lu's (2016) computational approach used a user's network information to determine whether an account is a bot or a human on Weibo. Thus, they identified "millions of spammers" (Zhang & Lu, 2016, p. 14). The downside of their strategy is that they can only identify spambots depending on someone's network. Another approach, that of Hegelich and Janetzko (2016), is based on the URL that a tweet was sent from, which can be retrieved as part of a tweet's metadata. By manually identifying tweets sent from obvious bot creators, such as Twifarm, they searched for accounts that followed these bots in order to unveil bot-networks. This approach is only possible if one starts with hashtags and tweets, not with Twitter accounts, because account metadata contains no URL information. The downside is that this method only detects a small number of active bots. For instance, in Hegelich and Janetzko's case study, only 1,740 bots followed one another. Another approach is to identify and single out behavioral aspects that differ from human users, such as a high frequency of messages sent. Various studies on campaigns (Howard & Kollanyi, 2016; Neudert et al., 2017) came from a group of scholars who count any account that sends out more than 50 tweets per day as bot, assuming "high automation." Needless to say, it is possible for a person to send 50 tweets per day (Musgrave, 2017). Also, not all bot accounts are this active, since passive bots exist only to boost certain accounts' follower numbers. Thus, this approach can only capture a specific bot type that broadcasts very actively. There is also the strategy of detecting social bots via near-duplicate tweets (copies or very similar versions of the same tweet sent by multiple bots), which bots use to inflate certain topics' frequency and importance (Schäfer et al., 2017). While this detection method is very useful, it remains unclear whether humans copied and pasted a tweet's content (Musgrave, 2017). Even if these copy-and-paste users were bots, they discover only one type of active copy-bots. Another share of studies uses multiple indicators to detect social bots: more elaborate ones use indicators such as "tweets to user," "mean tweet to retweet," "common words in the username," or "ratio of outbound to inbound @-mentions" (Bastos & Mercea, 2017, p. 6) to capture more than simple automated accounts. A similar approach, by Guo and Chen (2014), with a focus on geotagged tweets, proposes four steps to identify spambots, including machine learning techniques. A drawback is the focus on geotagged tweets, because many Twitter users opt out of this option. Although very elaborate, these techniques are hardly reproducible, since they require programming skills, which many social scientists (like us) lack.

With any bot-detection method, scholars face two key problems: (a) the cat-and-mouse game between bot creators and bot-detection developers and (b) the limited availability of data from commercial platforms. With complete data sets, it should be easy for platform owners to detect bots, but the incentive to do this and to delete these accounts is perhaps not worth pursuing: bot accounts do not buy anything and have no value for advertisers, but they keep the user numbers high. A sudden drop in platform users may unsettle shareholders. Thus, scholars must make the best of a tough situation. Here, we use the bot-detection tool Botometer, which was developed and maintained by computer scientists; it checks more than 1,000 variables of an account for features that are typical for bots (Davis, Varol, Ferrara, Flammini, & Menczer, 2016). This tool has been used in previous studies and is currently the most sophisticated, reliable, and available instrument for bot-detection (see the next section on methods). Botometer is open for other scholars to detect social bots on Twitter so as to replicate our analysis.

Data and Methods

We collected data on all Twitter accounts that followed the five German parties represented in parliament: conservative CDU and CSU, social-democrat SPD, socialist Die Linke, and environmentalist Die Grünen. We also studied the liberal FDP, and right-wing populist AfD, which were considered likely to successfully (re-)enter Germany's Parliament in 2017 (and did). There were two data collection waves: the first, before campaigns started in January and February 2017, and the second, during the week before Election Day on September 24, 2017.

For both waves, we first downloaded the Twitter account data of all followers of the seven German parties, including metadata such as their Twitter ID, screen name, and numbers of followers, following, and tweets (via BirdSong Analytics). Metadata also included information on account activity (i.e., whether or not a follower had been active in the past three months—whether he or she tweeted, retweeted, liked, or replied to a tweet). Downloading took place between January 1, 2017, and and February 13, 2017, for the non-election period (1,180,362 accounts), and from September 12, 2017, to September 14, 2017, for the campaign period (1,588,213 accounts).

In the second step, we used Botometer to identify bots and distinguish them from humans in an automated analysis via Botometer's API (Python 3.5). Since social bots constantly change their appearance, they are complicated to detect (Thieltges, Schmidt, & Hegelich, 2016). Botometer is a publicly available bot-detection instrument created and maintained by computer scientists at the University of Indiana. At the time of our study, it was the most sophisticated available instrument and has been used in several academic research projects, both by the creators and other scholars (Bessi & Ferrara, 2016; Ferrara, 2017). To ensure quality and comparability between the two waves, we kept in close contact with the computer scientists who maintain Botometer (and are greatly indebted to them for their kind support). However, we need to stress that bot-detection is not an exact science, and Botometer also comes with serious limitations, which we detail next.

Botometer "generates more than 1,000 features using available metadata and information extracted from interaction patterns and content" (Davis et al., 2016, p. 2). These are grouped into six main classes (Varol et al., 2017): *user* features include the number of followers and tweets produced by users; *friends* encompasses follower-friend relations such as retweeting and mentioning behaviors among one another; *network* characteristics include in-strength and out-strength (weighted degree) distributions, density, and clustering; *temporal features* relates to the analysis of average rates of tweet production of a user over various time periods; *content and language* features include statistics about length and entropy of tweets and part-of-speech tagging; *sentiment* features encompass arousal, valence and dominance, happiness, polarization, strength, and emoticon scores (see Varol et al., 2017). From these, Botometer calculates a probability score between 0 (human) and 1 (bot) for each Twitter account. Overall, the tool has an accuracy of 0.86 and suggests that between 9% and 15% of all Twitter users are bots (Varol et al., 2017). Because the tool is better equipped to identify humans than bots, our threshold for bots should be fairly high; not all accounts with a probability score over 0.5 should be counted as bots.

We conducted Step 3, data manipulation and cleansing, in R (R Core Team, 2017). Botometer could only evaluate about half of the Twitter accounts: 54% of followers in the non-electoral period (N = 638,674) and 53% of followers in the campaign period (N = 838,026), which constituted our sample (see Tables 2 and 3). Three errors prevented Botometer from calculating a final score for the remaining 541,688 follower accounts in

Table 2
Data of the non-electoral period (January 2017 to February 2017)

	Number of Followers (Total)	Final Data	Error (Sum)	Error: No Timeline	Error: Page does not exist anymore	Error: Not authorized
AfD	47,534	**31,885**	15,649	11,946	12	3,691
CDU	161,025	**88,207**	72,818	61,766	796	10,256
CSU	123,324	**60,795**	62,529	56,607	36	5,886
FDP	148,311	**75,470**	72,841	66,119	33	6,689
GRÜNE	290,679	**160,152**	130,527	115,769	144	14,614
LINKE	155,599	**86,447**	69,152	61,324	57	7,771
SPD	253,890	**135,718**	118,172	105,423	191	12,558
Sum	1,180,362	**638,674**	541,688	478,954	1,269	61,465

Note: Numbers are bolded to indicate the most important column in the data.

Table 3
Data of the campaign period (September 2017)

	Number of Followers (Total)	Final Data	Error (Sum)	Error: No Timeline	Error: Page does not exist anymore	Error: Not authorized
AfD	74,923	**44,912**	30,011	24,541	228	5,242
CDU	221,114	**118,446**	102,668	89,469	306	12,893
CSU	166,631	**81,389**	85,242	76,875	221	8,146
FDP	244,624	**119,124**	125,500	114,340	337	10,823
GRÜNE	356,481	**192,472**	164,009	146,104	358	17,547
LINKE	200,089	**110,578**	89,511	78,956	332	10,223
SPD	324,351	**171,105**	153,246	137,192	353	15,701
Sum	1,588,213	**838,026**	750,187	667,477	2135	80,575

Note: Numbers are bolded to indicate the most important column in the data.

the non-electoral and 750,187 accounts in the campaign phase: (a) an empty timeline (478,954/667,477 accounts), (b) the deletion of a Twitter account in the days between data collection and data analysis (1,269/2,135), and (c) privacy settings not authorizing access to run an analysis (61,465/80,575). This points to a serious limitation of Botometer. While social media platforms monitor their users' behavior and remove suspicious accounts such as social bots (Lorenz, 2018), external bot detection tools struggle with the platform's API access and its corresponding restrictions. Botometer cannot include a user's past activity in its analysis (when a user deletes all previous activity, Botometer cannot calculate a score). In addition, Botometer's access is limited by the user's privacy settings (bots may hide behind the veil of strict privacy settings). This leaves us with a specific kind of account: Twitter accounts with weak privacy settings, which were not deleted between data retrieval and the completion of analysis, with at least one tweet, retweet, or like. However, it should be underlined that all current bot detection tools and methods are imperfect. Despite these limitations, Botometer is a not-for-profit, academic project that has been and is widely used (e.g., by the Pew Institute), publishes about how it works, and is based on a multitude of possible indicators—which makes it a viable tool for the purpose of this study.

To allow direct comparability between the different number of party followers and the metric scale scores, we calculated probability density functions (PDF), which we present as density plots. To answer RQ1 through RQ5, we set the threshold for detecting bots depending on the density plots and accuracy of Botometer.

For a content analysis of messages that bots disseminated (RQ5), we selected the 100 most active bots (number of tweets sent) and the 100 most popular bots (number of followers). Both vary significantly from the general bot population and represent the peak of the long-tail distribution of bots' activity and popularity: While the 100 most active bots sent on average 94,920/113,200 tweets (non-electoral/election period), the average of all bots was 171/120 tweets. The 100 most popular bots had an average of 45,950/81,520 followers, whereas the average of all bots was 106/90 followers. With this focus we investigate two very specific types of bots: the most popular bots, which could potentially function as opinion leaders reaching a large number of Twitter users, and the most active, which could potentially flood the Twittersphere with political content. After having downloaded their tweets for the extended non-electoral period between January 2, 2017, and April 2, 2017 ($N_{(\text{active})}$ = 60,262, $N_{(\text{popular})}$ = 42,425), and the extended campaign period between June 24, 2017, and September 24, 2017 ($N_{(\text{active})}$ = 36,804, $N_{(\text{popular})}$ = 14,130), we extracted all hashtags used in these posts to assess the overall topics of these tweets (Bruns & Burgess, 2015; Small, 2011). The 100 most used hashtags for both the most active and most popular bots in both periods were manually coded by the authors. We analyzed 400 hashtags to assess whether they were political (e.g., ”Brexit), and checked the tweets containing the hashtag for verification. The pretest of 50 hashtags showed good reliability of the coders with a Krippendorff's alpha of 0.87.

Results

We compared the distribution of scores between 0 (human) and 1 (bot) across the seven German parties' followers. We found three different patterns in the non-electoral period; while in the campaign period, all parties except the right-wing populist AfD show a similar pattern (see Figures 1 and 2).

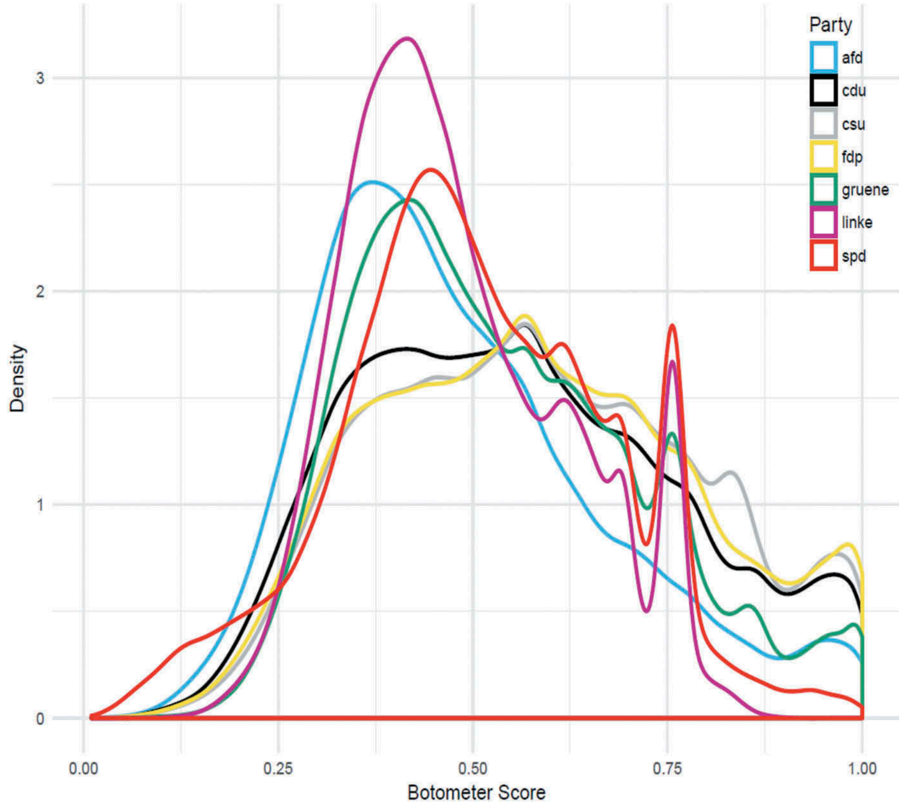

Figure 1. All followers' probability of being a bot in the non-election phase in a density plot (January 2017 and February 2017).
Note. Density plot of all seven German parties' followers and their Botometer scores in the non-election phase. $N = 638{,}674$, bandwidth = ndr0 (see Silverman, 1986). The area between two scores and the function = the probability of a follower receiving such a score.

During the non-electoral period, CDU, CSU, and FDP had a similar score distribution, as did SPD, Linke and Grüne; AfD showed a unique pattern. In the election phase, the general score distribution moved to the right, indicating a tendency of more bots among party followers. This is also true for AfD, whose follower distribution changed only marginally between the non-electoral and the campaign periods, although they gained more followers in the time between the two waves (+27,389 followers, +57%).

The strongest differences could be found regarding accounts that are most likely bots, followers with scores above 0.75. In the non-electoral period, SPD, Linke and Grüne showed a peak around 0.75, all other parties expressed a smaller peak between 0.85 and 1.0. During the campaign period, this peak between 0.85 and 1.0 was more pronounced for all parties. Notably, the probability density function pattern during the campaign period was very similar for all parties, except AfD. One reason for this, we discovered, is that most parties share followers. While AfD had about 45% single-party followers (followers that only follow AfD but no other party), the average share of single-party followers among all other parties was 17%. This means that approximately 83% of Twitter users in our data (whether human or bot) followed multiple parties. The share of single-party followers

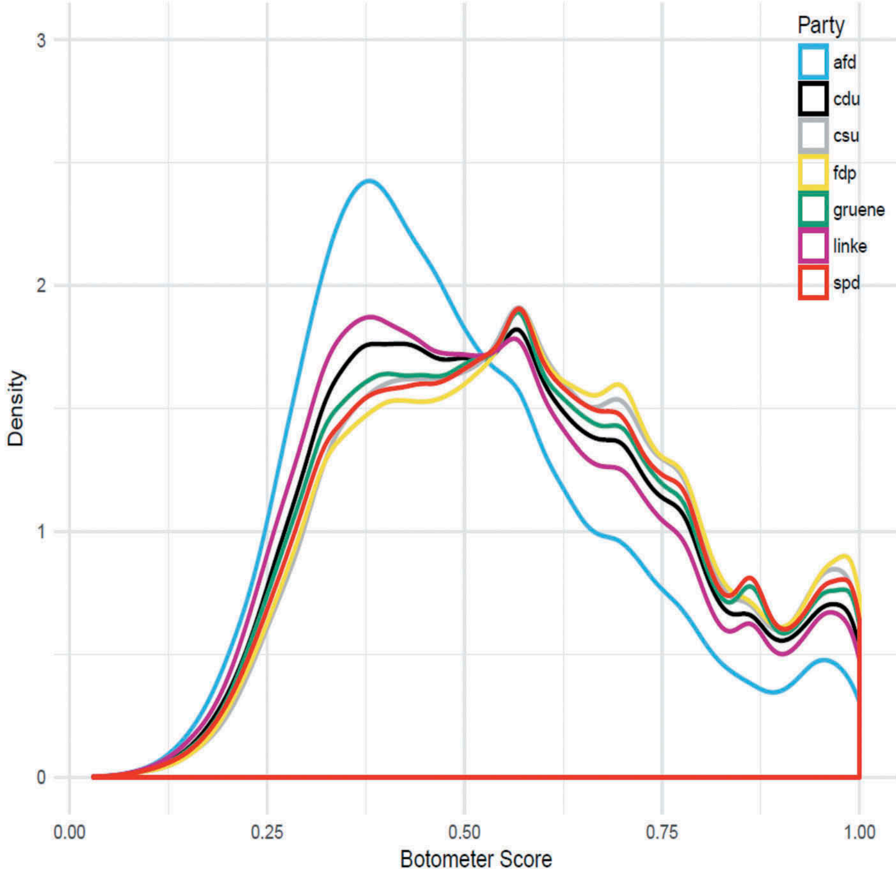

Figure 2. All followers' probability of being a bot in the campaign period in a density plot (September 2017).
Note. Probability density function (PDF) of all seven parties' followers and their Botometer scores in the election phase. *N* = 838,026, bandwidth = ndr0 (see Silverman, 1986). The area between two scores and the function = the probability of a follower receiving such a score.

decreased slightly from February to September (–2%), so during the campaigns, more followers chose to also follow other parties. This also indicates that a surplus of followers does not necessarily mean that more people follow parties on Twitter, but that people who already follow a party also follow other parties. Among the 407,851 new followers the parties acquired between February and September, only 79,272 (19%) were single-party followers.

Considering Botometer's accuracy, the hard task to distinguish between humans and bots in general, and the distribution of the scores in our two waves, we set the threshold for bots at a score of 0.76. We found that the share of social bots fall mostly in the expected range of 5% to 25% (RQ1; see Table 4).

Comparing the two waves, almost all parties had more followers, and most parties had more social bots among their followers in the campaign period than in the non-electoral period: AfD gained 0.4% more bots, Grüne 4.2%, Linke 8.3%, and SPD 8.2%. Some parties

Table 4
Bot presence and activity on Twitter in the non-electoral and campaign periods of Germany's 2017 national election

	Non-electoral Period		Campaign Period	
	Social bots among followers (%)	Active bots among social bots (%)	Social bots among followers (%)	Active bots among social bots (%)
AfD	3,181 (6.7%)	88 (2.8%)	5,325 (7.1%)	90 (1.7%)
CDU	16,419 (10.2%)	399 (2.4%)	21,981 (9.9%)	363 (1.7%)
CSU	13,759 (11.2%)	253 (1.8%)	17,238 (10.4%)	236 (1.4%)
FDP	16,180 (10.9%)	287 (1.8%)	26,087 (10.7%)	338 (1.3%)
GRÜNE	19,287 (6.6%)	196 (1.0%)	38,549 (10.8%)	485 (1.3%)
LINKE	1,696 (1.1%)	9 (0.5%)	18,734 (9.4%)	243 (1.3%)
SPD	7,212 (2.8%)	267 (3.7%)	35,697 (11%)	445 (1.3%)
Mean	**11,105 (7.1%)**	**212 (2%)**	**23,373 (9.9%)**	**314 (1.4%)**

Note: The means of the results are bolded.

had fewer bots during the campaign period: CDU –0.3%, CSU –0.8%, and FDP –0.2%. Overall, the mean share of social bots among the seven German parties' followers rose from 7.1% to 9.9% (11,105 to 23,373 social bots), but not for all parties (RQ2).

Of these social bots, an average of 212 (2%) were active during the non-electoral period and 314 (1.4%) during the campaign period. The numbers for each party are reported in Table 4. Social bots were not more active during the campaign period (RQ3).

Regarding RQ4, whether the populist party AfD had the highest number of social bots among its followers, our analysis revealed that during the campaign, AfD actually had the smallest share of bots among its followers (7.1%, 5,325 social bots). In the non-electoral period, AfD had a below-average share of social bots (6.7%, 3,181). However, AfD bots were particularly active: AfD had the second highest share of active social bots, with 2.8% during the non-electoral period and 1.7% during the campaign period. The data suggest that AfD had a larger share of human scores than all the other parties (scores lower than 0.4), a much higher share of active followers (33%/26% compared to an average of 15%/14.5% for the other parties), and the highest share of active humans.

Finally, we analyzed the content of the tweets from social bots in the non-electoral and the campaign periods. Of the 100 most frequent hashtags distributed by social bots following a German party in the non-electoral period, the popular bots used 13 political hashtags (the frequency of a hashtag's use ranged from 34 to 2,375, median = 71.5) and the most active bots 30 (the frequency ranged from 30 to 1965, median = 65.5). With one exception, these political hashtags did not refer to German politics. They covered issues concerning politics in Austria, the European Union (without a focus on Germany), France, Great Britain, Nigeria, and the United States. The one exception was one very popular bot that distributed the hashtag ”AfD to promote its political agenda, with a total of 53 tweets. Most nonpolitical hashtags and tweets were advertisments (ads for jobs, paintings, financial investments, etc.).

During the campaign period, the use of political hashtags decreased. Of the 100 hashtags analyzed for each set, the most popular bots used only seven political hashtags (the frequency ranged from 12 to 2,263, median = 23), the most active bots only eight (the frequency ranged from 42 to 1,916, median = 73.5). Again, none of the political hashtags referred to German politics; most concerned U.S. finance and climate change politics (such as #MisesInstituteUSA, #;DavidStockmansContraCorner, #environment, #green, #climatechange). Fewer hashtags related to Nigerian politics (#Biafra). Similar to the non-electoral period, most hashtags had a promotional purpose (#yoga, #realestate, #porn, #software, etc.) in the campaign period.

Regarding RQ5, neither the most popular nor the most active bots tweeted more political content during the election campaign than during the non-electoral period. However, we need to be cautious and cannot generalize from the 400 most active and most popular bots, because they are not representative for the overall bot population. It may well be possible that bots did not include one of the 400 most used hashtags in their political tweets or that they actively disseminated electoral propaganda without following a political party and would therefore not be included in our data.

Discussion

Social bots in the digital public sphere pose at least three challenges for political communication research: theoretical challenges to established concepts of social science, empirical challenges of detection and the measurement of impacts, and methodological challenges to the general validity of popularity cues and social media analysis.

In summary, we analyzed Twitter follower accounts of seven German parties before and during the 2017 electoral campaign. The analysis confirmed previous studies by showing that the share of social bots among these parties' Twitter followers increased from 7.1% to 9.9% during the election campaigns. Three research questions resulted in findings diverging from previous studies: the share of active social bots did not increase during the election campaigns; AfD did not have more bot followers than the other parties —on the contrary, it had the smallest share; and the bots that we identified distributed almost no hashtags connected to German politics. These findings have significant implications.

Connecting our findings to Ferree and colleagues' (2002) four normative models of the public sphere, the potential damage caused by social bots in election campaigns covers a spectrum of problems. From a representative-liberal perspective, the results show that bots caused a quantitative misrepresentation of popularity, because roughly 10% of Twitter followers were bots disguised as humans. In particular, in the case of SPD and Linke, the share of bots among followers increased by more than 8% during the campaigns. Thus, their follower growth of 22% each appears bigger than it really was if we only accept humans as authentic followers. Thus, social bots did manipulate popularity cues, disturbing the principles of proportionality and transparency during the campaigns. However, their impact remains purely in numbers, because we found hardly any political content spread by bots that related to the election. From a participatory-liberal and discursive perspective, it is interesting that the share of bots increased during election campaigns. In this tradition, the focus is much less on elections than on popular inclusion and authentic debate with genuine contributions at all times. The share of active bots (bots that like, share, comment, and discuss) was very low: 2% and less in both waves. While the proponents of participatory-liberal and discursive understandings of public spheres would not exculpate bots as non-authentic participants in political debate, the low bot activity and their predominant distribution of nonpolitical content would certainly be a consolation for them. From a constructionist perspective, the low bot activity is a greater reason for concern. Seeing it as crucial to include previously silent, marginalized voices in public discourse, the presence of software actors deliberately designed to manipulate popularity cues or contributions totally undermines the notion of a public sphere, whether during an election campaign or at any other time, whether or not they are active.

Another interesting, perhaps peculiar pattern that begs for theoretical reflection relates to right-wing populist AfD. In line with current literature pointing to the rather thin empirical evidence for echo chambers (Dubois & Blank, 2018; Fletcher & Nielsen, 2017), the increase of multiparty followers in the electoral period indicates that echo chambers are indeed rather unlikely in the broader population of Twitter followers of German political parties in general. It rather seems that people who already follow one or more parties on Twitter tend to expand their following to more parties during the campaigns. Thus, to some extent, the parties in our sample share the same followers, and the number of followers increases in the second wave, because followers follow more parties during the campaigns than before. AfD, however, varies significantly from this pattern: AfD has by far the largest share of active followers (about twice as many as the other parties) as well as by far the highest share of single-party followers (45%, so about half of the AfD followers follow AfD only). Also, bots among AfD followers were particularly active. This can be read as an indicator that echo chambers are more likely to be found among AfD followers, may they be bots or humans. AfD followers seem to be much less interested in other political parties and to a much stronger degree form networks of like-mindedness.

From our descriptive data on bot presence and activity we cannot judge whether they caused any actual harm to the campaigns and the electoral process. We should also not forget about human actors who actively manipulate public discourse on Twitter. Other reports on the same election, which focused on other data (hashtags), found that “traffic about the far-right Alternative für Deutschland (AfD) accounts for a surprisingly large portion of Twitter activity given that party’s share of voter support” (Neudert, Kollyani, & Howard, 2017, p. 1). What we can say for sure is that bots were clearly present, and their omnipresence on social media platforms, combined with their role in other campaigns, should keep social media researchers alert, providing a sound reason to closely monitor their activities.

Methodologically, social bots challenge the validity of social media studies: if a large part of likes, tweets, shares, and comments originates from bots, how can results from quantitative studies measuring political actors’ interactivity and popularity on social media be validated? The findings show that even the increase in followers needs further differentiation: Are new followers really “‘new”? Are they even persons? We propose that a standardized test for bot activity should become part of empirical studies about political communication on social media, in order to ensure results’ validity. To address this challenge, social scientists must cooperate with computer scientists and push for more and better tools to monitor bot activity on social media platforms. This also entails a more critical stance toward the validity of data from social networks—a key question for research quality, and not only in political communication. When large numbers of interactions on social media platforms are generated by bots, this must be reflected in the results and conclusions of studies based on this data type—for instance, network analyses of political actors or analyses of campaign communication on social media platforms.

As with all single-case studies, this analysis has limitations. We examined only one election campaign, in one country, on one platform, with one bot detection tool. Future studies should compare various countries and compare their findings with different bot detection tools. One could also start with hashtags instead of follower accounts. Analyzing hashtags would by default include exclusively active accounts that actually tweet, so that Botometer should perform better in such a design. Bot-detection is neither 100% accurate nor could it, in our study, deliver scores for about half of the accounts in our data set. Building social bots that mimic human behavior and building tools to identify them is a cat-and-mouse game. There is uncertainty about the accurate identification of bots; followers with a score around 0.6 remain hard to classify. The gray area is even larger when including Twitter accounts that produced an error: almost 89% of them had never sent a tweet ("no timeline error"). Is the sole purpose of these dead accounts or bots to make parties appear more popular than they really are? How many of them sent tweets but removed them before we could analyze the account? How many of them did not follow any political party but tweeted in favor of them? How many of the accounts with strict privacy settings, which we were not authorized to analyze, were bots actively tweeting?

Clearly, we need more empirical research into bots, and their activities and impacts. Future studies should ask how Internet users make sense of and construct perceptions of reality from their online interactions. How much do they know about social bots' presence and activity? Are they aware that they are interacting with social bots? Do they recall instances of interaction with bots? What are their perceptions of and opinions about social bots? Because people know what they know and what to think about from mass media (Luhmann, 2000), scholars should also analyze how journalists cover social bots. Are bots on media agendas? How is coverage about bots framed (as a technological phenomenon or a social issue)? Finally, researchers must remain alert to social bots and their influences on established theoretical concepts, digital empirical data, and current methods when analyzing digital communication.

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No potential conflict of interest was reported by the authors.

Supplemental Material

Supplemental data for this article can be accessed on the publisher's website at https://doi.org/10.1080/10584609.2018.1526238.

Note

1. Original quote: “Gerade für junge Parteien wie unsere sind Social-Media-Tools wichtige Instrumente, um unsere Positionen unter den Wählern zu verbreiten.”

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