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Social Bots' Role in Online Political Communication – Evidence from German Federal Election 2021

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Social Bots‘ Role in Online Political Communication

– Evidence from German Federal Election 2021

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Abstract

In 2016, the US elections and Brexit changed the perception and understanding of how social media platforms could influence political outcomes. This has been complemented by the advancement in automation and data processing. This paper studies the influence of bots on online information diffusion and political discourse around the 2021 German Federal Elections. It examines the behavior of social bots in online political communication, in particular, whether the presence of bots leads to an amplification of the Tweet volume of humans. Using Twitter data pertaining to the German political sphere over 6 weeks till election day, I find 6% of the tweets originated from bot accounts. The impact of the bots is investigated through time series analysis. The key findings are that the bots' tweet volume significantly impacts the human tweet volume, especially when the tweets hold the same inclination towards a political party. The influence is not always observed for across-inclination tweet volumes of bots on humans. Furthermore, employing impulse response functions, the impact is observed to be positive, indicating an amplification effect of bots' tweeting activity.

JEL classification: D72; D83; D84; C32.

Keywords: Political communication, social bots, Germany, Twitter.

1. Introduction

Over the past few years, social media and information technology have gained significance in political communication and information sharing. In addition to the general public, many media channels, politicians and public representatives, and analysts resort to social media to find the latest information, trends, and communication networks (Santana and Hopp, 2016). Political parties and candidates have increasingly turned to social media platforms for campaigning, sharing information, and initiating political discourse among their audiences (Vergeer, 2015). It can be readily used as their first point of contact with the public since the absence of a middleman makes it economical and faster and facilitates its reach to the non-traditional audience as well. Thus, it provides a direct and personalized channel of communication where the public can get a direct impression of the political candidates' characteristics and ideas (McGregor, 2018). Furthermore, campaigning on social media provides political candidates with more autonomy in setting out their political agenda (Conway, Kenski, and Di Wang, 2015). They can put out their agenda without getting screened through the structural requirements or the filters. They can also reach a wider audience irrespective of the public's pre-existing ideals and opinions as would be the case with traditional media where certain channels on the TV or Newspapers support a particular political ideology. For example, Fox News backing for the Republic party in the US compared to CNN favored the Democratic party (Bernhardt, Krasa, and Polborn, 2008). By eliminating any intermediaries and formal channels of news broadcasting, the pace of information dissemination on online social networks has increased manifold. Therefore, more and more political parties and candidates have been turning to social media to reach out and engage with the public.

Twitter is one of the most prominent platforms for news sharing and online political discourse. It has been at the forefront of several socio-political discussions and campaigns (Jungherr, 2016). Whether, it is used by politicians such as Donald Trump, the ex-President of the US, or by the public in political and social movements or protests, e.g., the South African #RhodesMustFall movement[1] (Bosch, 2016); it has been gaining significance and attracting attention. The quality and influence of the information shared on Twitter have been discussed and studied in many spheres and research disciplines. Twitter, like other social media platforms, provides a faster and easier channel to promote nonverified information or misinformation and fake news with potentially hazardous ideas and opinions. Thus, it can be afforded both a positive as well as a negative role depending on the case and use. While it may have enabled many powerful online movements, it has nonetheless received censure for not protecting its users against fake news, spam, and concealed automation in the form of bots.

Bots, or social bots as they are more popularly referred to in the literature due to their nature and role, refer to those profiles or accounts on social media networks that gather information from the internet to create human-like profiles. Speed and anonymity help the bots to manipulate the flow of information, spread misinformation, and overshadow the correct information on these networks.

Several factors play a role in making people susceptible to bots' interference in the flow of information and political discussions. First is the reinforcing nature of social media for filter bubbles that fortifies the relevance and authenticity of the information. That is, through sheer

[1] The Rhodes Must Fall movement was a campaign initiated by students at the University of Cape Town to demand the removal of the statue of Cecil John Rhodes, a British colonialist.

recurrence and deficient safeguarding policies and efforts against the distribution of misinformation on social media sites. Second is the abundance of information and an individual's cognitive limits (Simon, 1955)[2]. In an attempt to strike a balance between cognitive effort and achieving a sufficient desirable outcome, individuals tend to depend on cognitive heuristics to make political assessments and judgments (Lau and Redlawsk, 2001). Moreover, given that everyone may not be adept to employ cognitive shortcuts to reach the best decisions, it may lead to biased evaluations, especially when faced with misinformation. Third, despite the deliberate nature of fake news, the mechanism of being spread by other social media users consisting of one's family members, friends, and peers shrouds the regard for correct information or the manipulative intent. (Azzimonti and Fernandes, 2018). Bots can use these features to their advantage and exacerbate the given phenomena by bringing in the aspect of anonymity and speed in the diffusion of information. Thereby, taking advantage of the cognitive biases that people display in information processing. Besides, by the time any measures can be taken to rectify the misperceptions created or to remedy the aftermath, misinformation would have already done the damage. Anonymity further facilitates this spread without anyone being held accountable for it.

The problem, in particular, lies in the fact that bots are not transparent about their identity. Even if their actions are not entirely malicious, their mere presence is worrisome as it can impact the authenticity of online communication. They can stage non-real hype, spread misinformation, and

[2] Information overload and cognitive limitations during the fast processing of information can make individuals vulnerable to misinformation. Although, a rational individual is assumed to be fully informed to make a well-thought-out choice, the decision-making process, in reality, is not as well defined and organized. That is, information and reasoning constraints impose limitations on an individual's ability to process information, thereby, indicating bounded rationality (Simon, 1955) .

overwhelm the regular information flow. Therefore, by limiting the authenticity of online political communication, bots can nonetheless have a real and valid impact on human users' political behavior and decisions. This has been found in many political events, such as the US presidential election of 2016, Brexit (Woolley and Guilbeault, 2017; Gorodnichenko, Pham, and Talavera, 2021), conflict of Russia in Ukraine in 2014 (Hegelich and Janetzko, 2016), 2014 presidential elections and the 2016 impeachment proceedings in Brazil (Arnaudo, 2017), etc.

This paper studies the impact of social bots' activities on political communication on Twitter concerning the German general elections in 2021. The focal question is whether the presence of bots leads to an amplified spread of information, in terms of the volume of tweets and retweets and a higher response of human users. Moreover, it studies the activity and behavior of bots depending on the inherent party support in the messages posted and shared by them.

These questions are addressed by examining a dataset of Tweets collected from the Twitter Streaming API in real-time, over 6 weeks leading up to election day. This novel dataset provides insight into the German online political sphere before the federal elections of 2021 with interesting trends and party support. Furthermore, the dataset not only contains tweet texts but also other information such as the users' profiles and accounts information, etc. The tweets are, thus, classified according to their originator (based on the account information), and party inclination (based on the text of the tweets). To examine the influence of bots, like Gorodnichenko et al. (2021), I am applying a time series analysis. Employing VAR (Vector Autoregression), I find bots to have a significant influence on online political communication. In particular, the bots' tweeting activity has an amplifying impact on the human tweets, especially when both the human and bot tweets hold the same inclination for the given party/ies.

This paper proceeds with a literature review in chapter 2, and predictive theory and research questions in chapter 3, followed by an overview of the data collection, processing, and description in chapter 4. Chapter 5 discusses the methodology employed in the paper. Findings are presented in chapter 6, followed by a discussion and conclusion in chapter 7.

2. Literature Review

2.1. Social Bots – Nature and Role

The general consensus about social bots is that they are automated, algorithm-run agents that can anonymously operate and interact on social networking sites. They are designed to gather information over the internet to create human-like profiles and social media activity (Woolley and Howard, 2017; Howard, Woolley, and Calo, 2018). There are differences of opinion in the literature regarding the autonomy of social bots. While the majority of the literature considers bots to be autonomous agents (Duh, Rupnik, and Korošak, 2018), some studies (e.g., Assenmacher et al. 2020) consider the presence of human intent behind the bots' actions and agenda as a contradiction to their autonomous identity. The justification presented by the latter studies is that social bots are nonetheless initiated by their botmasters and despite the sophistication, their actions are broadly led by the agenda set for them by the human botmasters. On the other hand, bots are seen as self-reliant in the sense that they can interact with and learn from their environment (Duh, Rupnik, and Korošak, 2018). For example, by imitating the human temporal activity, i.e., respecting the day-night difference for tweeting activity, etc. (Grimme et al., 2017). Assenmacher et al. (2020) argue that the sophistication and intelligence of social bots can be attributed to their characteristics to avoid detection and not the complexity of the tasks that they perform.

Social bots' abilities can extend from the simple tasks of sharing and liking content to producing their own content and communicating anonymously with other unsuspecting users (Assenmacher et al., 2020). Though the latter type of social bots are considered more dangerous in the sense that they can potentially manipulate online content (Assenmacher et al., 2020), the former type of bots can nonetheless influence the online discourse by amplifying certain information or ideas. In the sphere of political communication, they do so intending to influence public opinion. Some political scientists and researchers (Woolley and Guilbeault, 2017; Woolley and Howard, 2017; Howard, Woolley, and Calo, 2018) have taken it one step further and coined a further term, political bots, to describe the social bots' role in politics and political communication. Here onwards in this paper, the social bots with the specified characteristics will be referred to as bots.

While the bots may be used by mass media representatives or other such entities on social media to quicken the pace of information distribution or other well-meaning tasks, their reference in the present context is mostly malicious. That is, they are designed to misinform, misrepresent, mislead, and manipulate the public. For example, to spread misinformation or to overwhelm the networks with noise to drown out any sensible political discussions and useful information. Similarly, they can be used to increase followers on Twitter to appear popular (analogous to getting paid agents to inflate the number of attendees at a political rally), and to manipulate human opinions and beliefs with biased and censored information and projections (Ferrara et al., 2016; Howard, Woolley, and Calo, 2018).

2.2. Who are behind bots?

Despite the relative autonomy and sophistication, bots are nevertheless provided with some code to accomplish the objectives set out for them (Keller and Klinger, 2017). According to

Assenmacher et al., (2020) social bots are provided with a technical foundation, which enables them to create a profile, interact and connect with the platform's API (Application Programming Interface), and an algorithm that roughly outlines their behavior and online activities. As described in the previous subsection, these activities can differ based on the level of intelligence, and also their overall prescribed goal (Assenmacher et al., 2020). Bots have been found active in various political events, under various political regimes (Woolley and Howard, 2017). Thus, the objectives are set according to the political situation and target audience. For example, Woolley and Howard (2017) observed that authoritarian regimes, such as China and Russia, have made use of them against their own citizens as well as those of other countries. In the democratic systems (which is of interest in our case) various interest groups, such as political actors, lobbyists and other agents with political interests can be engaged in sponsoring and supporting the design and management of bots (Woolley and Howard, 2017). For example, multiple automated accounts on online social networks were found to be associated with a Brazilian Businessman who supported the election campaign in favor of Neves, i.e., an opponent of President Rousseff in the 2014 Presidential Elections in Brazil (Arnaudo, 2017). Forelle et al. (2015) found that in the Venezuelan Twittersphere, bots were employed by the opposition of the government. However, these bots were mostly found to assume the appearances of political organizations, parties, and government officials, and not the general public. These Venezuelan bots were tasked with creating or managing an impression of politicians by reporting on their performance in different public events etc. (Forelle et al., 2015).

Some studies have identified and analyzed foreign intrusion in various countries' online political communication during important political events (Woolley and Howards, 2017; Badawy et al., 2018). However, the categorization and differentiation of bots' initiators and sponsors have not been extended to the various interest groups. Rather the focus of research on computational propaganda and political interference using automation on social media has mostly been on the frequency, behavior, and agenda of these bots. Furthermore, bots must not follow an explicitly mapped-out sequence of instruction, rather they work with certain non-concrete guidelines (Hegelich and Janetzko, 2016). As signified in the definition of bots, they mostly follow a set of rules to mimic human behavior on these social networking sites (Hegelich and Janetzko, 2016, Keller and Klinger, 2017).

2.3. Bots in Information Flows and Political Communication

This study contributes to the literature on the presence, and impact of bots on online political communication. The presence and role of social bots in online political communication have been analyzed and acknowledged by various studies over the years (e.g., Forelle et al., 2015; Neudert, Kollanyi, and Howard, 2017; Woolley and Guilbeault, 2017; Boichak et al., 2021; Gorodnichenko, Pham, and Talavera, 2021).

As has already been noted, social bots present on Twitter can influence the political behavior of users in multiple ways. The most commonly observed and studied intrusion of bots in the social science literature has been in manipulating the spread of political information, i.e., by sharing links of news on Twitter (original tweets), amplifying the diffusion of information, and/or misinformation (retweets and shares). Shao et al. (2017) observed the role of bots particularly in the spread of misinformation. They found bots to not only quicken the pace and spread of misinformation but overwhelm the networks with noise to drown out any sensible political discussions and useful information. Furthermore, tagging influential users with possible misinformation helps substantiate the claimed misinformation (Shao et al., 2017; Azzimonti and Fernandes, 2018), thereby setting them up to go viral.

The online political sphere of the US has been of interest to many researchers since the 2008 US Presidential elections. Similarly, the popularity and use of social media for political discourse in the UK have also been significant in the past decade. Woolley and Guilbeault (2017) and Gorodnichenko, Pham, and Talavera (2021) have examined and confirmed the influence of bots within the realm of online political communication in the US and UK. Woolley and Guilbeault (2017) employed both qualitative analyses based on expert interviews and quantitative network analysis to investigate the bots' impact on online information flows during the 2016 US election. With the help of the retweet networks constructed using the tweets collected from the Twitter API during the election period, Woolley and Guilbeault (2017) concluded that the Twitter bots had an influence on the political conversation on Twitter during the elections. Gorodnichenko, Pham, and Talavera (2021) studied the influence of bots on human Twitter users' online political information processing and communication around the high-profile political events of the US 2016 General Presidential Elections and the UK 2016 Brexit Referendum. To understand the diffusion of the information steered by the bots, they created impulse response functions, by employing tools of time series analysis. The impulse response functions were used by them to investigate the vulnerability of a human user to the information posted by a bot, i.e., the number of times that the bot's post got retweeted or received any other forms of response, e.g., new posts in response to the original one. They found support for their hypothesis of echo chambers in online social networks. That is, the response of a Twitter user in the form of retweets, in their sample of the US and UK, was stronger and faster than the original messages of the other users with the same beliefs (pro-Trump/Clinton and pro-leave/remain).

The social bots' role in German politics has not been examined as much in comparison to the US and UK, but it is nevertheless significant. Keller and Klinger (2019) studied the Twitter followers of the top seven German parties around the 2017 German general elections and found the bots' share to be higher during the campaign period of the elections as compared to before. Furthermore, they examined the share of total bots and the share of active bots during the electoral and non-electoral periods. They noted that bots do not only pose a threat in terms of amplifying the spread of information but could set forth new and fictitious viewpoints. Similarly, Neudert, Kollanyi, and Howard (2017) analyzed the Twitter activity for bots and junk news around the 2017 German elections. While the share of bots in the Twitter data that they observed was small (7.4%), it was predominantly made up of AfD support. Boichak et al., 2021 studied the impact of orchestrated interventions, including but not limited to the employment of bots, in political communication and information diffusion on Twitter. They examined the diffusion of information in terms of speed, scale, and range by investigating the tweets of and around some prominent candidates during the 2017 German elections. They found the non-organic, orchestrated interventions to have an amplification role (in terms of retweeting) but not an effective diffuser of information (in terms of bringing new audiences/followers for the candidates). Furthermore, they observed the amplification of the messages by Alice Weidel and Sahra Wagenknecht[3] to be the highest among their sample of German political candidates

[3] Alice Weidel is the leader of the German far-right party AfD and has been the member of the German Bundestag (national parliament or the lower house) since 2017. Sahra Wagenknecht is a member of the 'die Linke' (the Left party).

(Boichak et al., 2021). While the studies on the German political sphere analyze the bots' behavior in various facets by investigating the networks between the users and the diffusion channels, they do not examine the impact through employing rigorous econometric analysis. This paper aims to bridge that gap.

Some studies have also investigated the influence of bots in non-election periods, for example, Forelle et al. (2015) in the Venezuelan political sphere; Hegelich and Janetzko (2016) around the Ukrainian-Russian conflict in 2014; Arnaudo (2017) during impeachment proceedings of former Brazilian President Rousseff; Bello and Heckel (2019) on the UK politics after Brexit. Bello and Heckel (2019) while analyzing the behavior of bots in the UK political sphere post-Brexit, used a reverse engineering method to investigate the strategies used by bots. That is, by observing the actions of the bots, their machine-learning model uncovered the type and sources of their shared content, their creators, location, and target audiences. By examining the strategies of the bots, Bello and Heckel (2019) attempted to comprehend the possible influence on the public's opinion.

3. Predictive Theory and Research Questions

Imagine an online platform for political communication and information dissemination, which can be accessed by the citizens/voters of a given country. Citizens can form their political opinions with the information that they come across from various sources, including the platform in question. They use this platform to participate in online political discourse. During the election period, the online platform contains posts pertaining to political parties, their candidates, election campaigns, and other associated information. The political parties' objective is to increase their vote shares. The political parties and their representatives can use the platform for campaigning to inform and persuade the voters in their favor. In general, being a subject of discussion is profitable for the parties. The volume of messages about a certain party or its candidates increases its visibility to the voters. Thus, a higher volume of messages on the platform is favorable for the parties. However, certain negative news, for example, a scandal, etc., especially at sensitive times such as the elections can also be detrimental to the parties. Therefore, a higher volume of positive messages can be favorable to the given party, and negative messages can be unfavorable to the given party while benefitting any opponent party/parties. Thus, parties can use the platform, along with other available channels, to influence the voters' opinions in their favor.

Bots by interfering with the online information flow and public discourse can influence online public opinion and eventually political decisions and outcomes. They can influence the political sphere through two channels. First, it can have an impact on the voters' opinions and behaviors. Second, it can influence the parties' political agendas and subsequently policies. Though the major political stances of the parties are announced and known much earlier in the campaign period, the political debate can have an impact on any new and upcoming plans that they propose. Though the focus of this paper is on the first channel, one cannot ignore the interaction that the public has with the political candidates online or the information that flows between them. Furthermore, while this paper assumes bots to be independent of the parties, the parties can nonetheless benefit from their online activity if it is in the parties' favor.

While bots draw on the cognitive limitations and the structure of the social media platform, phenomena such as the bandwagon effect[4] can strengthen their impact. For instance, by fueling

[4] Schmitt-Beck (2015) explained the bandwagon effect in the political sphere as success breeding success. That is, the public tends to support the political preferences and positions with a higher perceived majority.

the popularity of a certain party, bots can exploit the bandwagon behavior of the public into garnering further popularity and support for the said party. Similarly, bots can further augment the impact of filter bubbles and confirmatory bias of social media (Guriev, and Papaioannou, 2022) to make people believe that there are many people like us, fortifying their beliefs. Moreover, they can use emotions and negative information, as negativity and malice breed deeper and further. That is, damaging notions and impressions are more easily accepted and prove to be more resistant to later corrections (Baumeister, et al. 2001). Thus, bots can impact the political sphere by influencing the platform users – political candidates and the voters - and other citizens (off the platform) through the platform users. That is, the trending topics on the platform can be picked up by other media channels, or discussed by the platform users in their offline social circles, etc. Though I do not test for the offline impact in this paper, it would be plausible to assume that if the online information is not mere noise, then it can have a non-neutral effect in the offline world (voter behavior and election outcome) as well.

Considering Twitter as the said online platform, the focal question of the paper is, whether the presence of bots on Twitter leads to an amplified spread of information in terms of the volume of tweets of human users. Given a multi-party system, is the response of humans (in terms of the volume of tweets) to bots dependent on the inclination towards a given party? For instance, depending on the party inclination in the respective tweets, does the humans' response to bots increase if the tweets are pro or against a certain party?[5]

[5] It is worth noting that this is different from the question of echo chambers studied by Gorodnichenko et al. (2021) since there the researchers look at whether humans are influenced by bots from the other side of the ideological divide and vice versa. Whereas I am observing the party effect, that is for instance, whether the mention of AFD (pro or against) generates a higher response than that of CDU's mention. Similarly, is the response then supporting the original tweet's disposition or contradicting it.

4. Data

4.1. Data Collection and Processing

The data was collected in real-time using the filtered-stream endpoint through Twitter API v2. The filtered stream allows researchers to sift through and access the public tweets according to the filter rules assigned by the researchers. The filter rules employed in this paper consisted of keywords that were commonly used in Tweets pertaining to the German elections. The keywords were selected with the help of pre-study trials and observation of the political Twittersphere in June and July 2021.

Being a representative democracy, the decision-making process in Germany is delegated to the members of the parliament. Members of the parliament are chosen through a mixed-member proportional representation system, where each voter gets two votes: a direct vote for a constituency representative, and a secondary party vote. German parliamentary system employs a 5% threshold according to which only the parties that acquire at least 5% of the party (secondary) vote get to hold seats in the parliament. Six parties have so far made it to the parliament, namely: Christian Democratic Party (CDU)/ Christian Social Union (CSU)[6], Social Democratic Party (SPD), the Greens (Gruene), Free Democratic Party (FDP), the Left (die Linke), and Alternative for Germany (AfD). Each of the parties opt for a chancellor candidate before the elections, who in the case of the party winning majority votes would serve as the Chancellor of Germany for the next four years. The political campaigning is, thus, based on both the parties' agendas and initiatives, and the candidates' competencies and public approval.

[6] CDU and CSU are considered sister parties. While they have separate orginations and affiliations at the local level, they form a union at the federal level.

As noted by Boichak et al., (2021) the external actors in Germany, including bots, may be present and aim at the broader political conversations, and not limited to only the discussion about well-known candidates or the elections. Therefore, keywords were selected according to two major categories, electoral and topical. The electoral category further includes five subcategories: party acronyms, chancellor candidates, slogans and catchphrases, conspiracy-related hashtags, and keywords referring to the said German elections.

While most of the present literature has used hashtags to collect tweets, this paper takes on a broader perspective. It became evident during the pre-study analysis of the Twitter traffic that a large fraction of the tweets that were relevant to the political discussion in Germany did not include the expected hashtags. Therefore, the party acronyms have been included both with and without hashtags. Moreover, an additional language restriction was added to the party acronyms without hashtags. This was needed since while these acronyms popularly refer to the political parties in Germany, they are not exclusive to them when the other languages are in the mix. Furthermore, while the broader selection criteria of the keywords without hashtags is pertinent in attending to the missing data concerns, it does however present challenges of its own. When a keyword is part of a hashtag, e.g., #AfD, Twitter API recognizes it as a hashtag and returns only those tweets that contain that specific hashtag. Whereas, in the case of keywords without #, the Twitter API returns any tweets that contain that keyword in the text, author's id, author's description, links, or any of the other fields in the tweet. Thus, for example, using keywords such as 'Weidel'[7] could result in unrelated tweets being picked up.

[7] Alice Weidel is the leader of the German far-right party AfD and has been the member of the German Bundestag (national parliament or the lower house) since 2017.

To ensure that the significant Twitter discussion about the parties or the chancellor candidates was captured, certain popular/trending hashtags were included in the keywords list during the data collection phase. Doing so also facilitated keeping up with the fast-shifting dynamics of social media platforms and new trends corresponding to online and offline political debates. The addition of new hashtags was allowed given that a pre-defined selection criterion was satisfied. The criterion first required that the hashtag fit the category of slogans and catchphrases. Secondly, the volume of tweets containing the given hashtag needed to be 15% of the overall volume of tweets belonging to the category of slogans, i.e., the set of hashtags initially approved.

4.2. Tweet Object

The collected tweets in addition to the content of the tweet such as text, hashtags, and links, also contain information about the type of the tweet, language of the tweet, author of the tweet, referenced tweets, etc. Tweets can be either original or referenced. Original tweets are essentially tweets posted without any link or reference to a prior/already existing tweet[8]. Referenced tweets are tweets that are linked to a certain original tweet. Three types of referencing behavior are recorded for the tweets, i.e., replying, retweeting, or quoting. Retweets and quotes appear on the timeline of the person retweeting and quoting them; while replies can be found, in addition to the sender's timeline, in the notifications and timeline of the receiver (as a reply to one of their tweets). However, they are visible to anyone who is following both the receiver and the sender of the reply, or if the tweet (reply) is relevant to them according to Twitter's algorithm[9].

[8] Original tweets are not considered original in terms of their content, as content could also be a rearranged version of another tweet or even a copy. Rather, it refers to the tweet being an initiator for a chain of referenced tweets.
[9] The Twitter adds content to its users' timelines not yet chosen by the users based on its algorithm's determination of the users' network and activity, etc. (Twitter help center docs)

Therefore, the audience and reach of the given types of referenced tweets are also accordingly different.

4.3. Data Description

The data was collected over six weeks, from 6:00 am on August 12, 2021, until 6:00 pm on September 26, 2021. During this time, a total of 8,258,462 tweets were collected. 18.3% of the tweets are original and 81.7% of the tweets are referenced tweets, of which the highest percentage (53.4%) belongs to retweets. As mentioned before, the referenced tweets can be of three types, however, it is not always possible to achieve a clear-cut categorization of the tweet as only one type of referenced tweet. That is, a referenced tweet can be in some instances classified as a reply as well as a quote by the Twitter API since a reply can include a quote of another tweet.

This dataset contains tweets from a total of 403,013 accounts. Only 2.03% of the accounts in this dataset are verified by Twitter[10]. This suggests that the largest share of the tweets belong to the general public, including possible bots. Moreover, not all accounts were tweeting with a similar frequency in the given period, i.e., some of the accounts were more active than others. About 24.1% of the tweets are from users who have tweeted more than 500 times throughout the dataset.

As expected from the pre-trial observations, a large volume of tweets is without hashtags. That is, only 48% of the tweets contain hashtags in the text of the tweet. However, due to the large

[10] Twitter verifies the accounts held by known personalities and organizations. This data was collected before the application of the fee for verification of the accounts. Therefore, getting a verification had no drawbacks for people who qualified for a verified account.

size of the data set, the tweets with hashtags amount to almost 4 million tweets. A total of 196,468 unique hashtags were recorded, where the hashtags with a frequency equal to or more than 500 in the dataset were analyzed and used for classification. A total of 420 of these hashtags can be assigned to one of the six political parties where 224 of them provide an inclination of pro or against the concerned party. For example, #Laschetverhindern (i.e., preventLaschet) relates to CDU with an against inclination, whereas #ichwähleAfD (IchooseAfD) is a pro-AfD hashtag. Furthermore, 957 hashtags are concerning the election or German politics in general but without a reference to any of the parties.

4.4. Bots' Identification

Botometer, a bot-identification tool, was employed to estimate the bot scores for each account in the given dataset. Botometer has been used by many studies examining political events, such as Gorodnichenko, et al (2021); Keller and Klinger (2019); Bello and Heckel (2019); and Shao et al (2017)[11]. Botometer estimates a score for a Twitter account based on various features and activity of the account, such as the account's profile, following characteristics, timeline activity, network structures, etc. Since the tweets in this dataset are all in German, I obtained the Universal bot scores that were estimated by Botometer using the account features independent of language. The Botometer Pro V-4, fundamentally, refers back to the Twitter Rest API to gather the account information that it requires to estimate the scores. Therefore, botscores were computed during the data collection process to make sure that all the relevant accounts were examined[12].

[11] Botometer has been progressing and advancing in terms of the underlying models to maintain the effectiveness of their bot classifier. For this paper, I have used the version v4 (Sayyadiharikandeh et al., 2020).
[12] It is not possible to compute bot scores for accounts whose information is discontinued from being publicly available for various reasons. Furthermore, the account information could be altered by their users or the access could be made private by their users, or simply removed by Twitter if caught against community standards.

4.5. Tweet Dynamics of Bots and Humans:

Around 8.3% of the accounts have a bot score of over 0.5, amounting to 6% of the tweets in the dataset[13]. Based on the information provided in the Botometer documentation, the botscores over 0.5, on a scale of 0 to 1, can be referred to as bot-like[14]. In the collected data, the mean of the botscores increased over time, i.e., the bot activity increased near the elections. Specifically, the percentage of the tweets coming from the bot accounts was the highest at 7.1% on the 25th of September (the day before the election day)[15]. The tweeting activity increases over time for both bots and humans. Three significant peaks in the overtime volume of tweets (figure 1) are observed on Aug 29th, Sept 12th, and Sept 19th, 2021 (or t-28, t-14, and t-7 respectively) that correspond to the TV-Triells (debate of the three top chancellor candidates on TV). Such debates are important campaigning events for the chancellor candidates as they get an opportunity to present and defend their policy views and plans. The public also gets to know not only their policy standpoints but also get an impression of their policy implementation and feasibility plans. The peaks suggest the notion that different types of media feed off of each other in terms of news and trends.

[figure 1 goes here]

The bot activity was found comparatively higher in the original tweets as compared to the referenced tweets. As already noted, original tweets refer to tweets that are unlinked to any

[13] Botometer provided a botscore for 99.3% of the tweets. Since the Botometer-v4 collects information from the Twitter API in real time for the classification, it cannot check for any accounts that are deleted or made private in the mean-time.
[14] I have not considered the accounts with the scores equating to 0.5 as bot-like, as that could comprise of the accounts with ambiguous results.
[15] From here on, for brevity we will refer to bot-like accounts as simply bots.

already existing tweets. This is similar to the finding by Gorodnichenko et al. (2021) about bots' ability to create content[16]. However, bots appeared more often for one of the categories of the referenced tweets, i.e., the bot accounts made up more of the reply volume as compared to the retweet volume (figure 2). This finding is opposite to the tweeting behavior observed for humans, who retweet more often than reply to other tweets.

[figure 2 goes here]

The most talked about party in the dataset is the CDU, followed by SPD, and then AfD. The volume of tweets for CDU and SPD is in line with the offline trends as well. The high volume of tweets related to AfD could be a confirmation of the idea that social media networks offer a platform for right-wing groups. While the main fraction of the tweets for each respective party come from humans holding a neutral inclination, the tweets with an against inclination for CDU make up a significant fraction (41.9% of the CDU tweets) (figure 3, panel B). Moreover, anti-party tweets are the highest for CDU while pro-party tweets are the highest for AfD in both the bot as well as the human traffic.

[figure 3 goes here]

As expected, the bot accounts have on average higher counts of following than followers, which is contrary to the observation for human accounts. This observation seems in line with that noted by Keller and Klinger (2019), that bots may be passive. For instance, such bots may have been created to amplify the follower counts of certain accounts. Furthermore, their tweeting activity

[16] It is possible that content posted in the original tweets is not original (novel), rather a copied or a remixed version of an earlier post. In any case, it serves the same purpose in the goal of spreading information to push certain beliefs.

is also in line with their average ratio of the following and follower counts. That is, as noted, bots have a higher volume of replies than retweets in the present dataset. Replies are directed to the originator of the tweet. Thus, a reply by being part of the thread of conversation will receive an audience, given that the originator has followers, even if the account posting the reply has few followers itself.

5. Methodology

5.1. Classification of Tweets

The unit of analysis in this study is the volume of Tweets. The classification of tweets is on two bases, i.e., bot- or human-like classification, and partisan classification. Tweets are either identified as human tweets or bot tweets based on the Twitter accounts that the tweets are coming from (as described in section 4.5). Furthermore, tweets are classified as pro or against one of the six major parties, as described before. It must be noted that due to the multi-party system, being pro a certain party does not necessarily make a tweet against another party and vice versa. In the literature that examines a two-party system or a binary decision (e.g., Gorodnichenko, Pham, and Talavera, 2021), it has been seen that a tweet pro a certain party is considered against another automatically. This overlooks the possibility that a person could be voicing an opinion against a certain party/decision without having any positive inclinations for the counterparty/decision. This paper, thus, takes into consideration that a person/tweet-originator must not necessarily favor a certain party - they could be against the entire construct, as substantiated by the presence of hashtags such as #nichtwählen (not vote), and #Wahlboykott (election boycott), etc.

The tweets are classified as pro or against a certain party with the help of the hashtags that appear in the text of the collected tweets. The hashtags were classified manually according to the inclination for a certain party and labeled as pro, against, or neutral[17]. For example, a tweet containing the hashtag #Laschetverhindern (#preventLaschet) is classified as anti-CDU, or a tweet containing #CDUwählen (#chooseCDU) is classified as pro-CDU. Based on the two classifications, tweets are classified into 36 categories. For example, a tweet coming from a bot account and containing hashtags labeled as pro-CDU is identified as bot-cdu-pro. The tweets that contained both the pro and against hashtags were left out of the analysis to avoid duplication and any possible spurious correlations[18].

5.2. Econometric Model

The focal question of this study, i.e., whether the presence of bots leads to an amplification of human tweets, can be addressed through the historical decomposition of tweets of bots and humans by employing a time series analysis such as Vector Autoregression (VAR) (Sims, 1980). By employing VAR, I investigate whether the volume of bots' tweets in period 't' have an impact on the volume of human tweets in period 't+1'. VAR proves to be a suitable model as it provides bi-directional causality, which is crucial to take into account while studying social media activity. That is, though the main objective of this paper is to observe the impact of bots' tweets on humans' tweets, observing an impact in the other direction can suggest a possible feedback effect and further reinforce the amplification effect of the bots.

[17] The hashtags that appeared in more than 500 tweets were used for the classification.
[18] These tweets were fewer in number in comparison to the rest of the tweets.

Employing VAR, the paper examines the impact of bots' tweets on the human tweeting volume while taking into account the party inclination of the tweets. For example, it investigates the response of pro-CDU human tweets to pro-CDU bot tweets or anti-CDU bot tweets, etc. This logic can be similarly applied to all six parties. Examining within-party impact suffices here, as the objective is to observe the tweeting behavior in response to a certain type of tweet; where a pro-CDU will invite either pro-, neutral- or anti-CDU tweets. Thus, the following VAR specifications are repeated for each of the six parties.

$$Human_t^{pro\_p} = \sum_{k=0}^{K} \alpha_{pro\_p,k} Bot_{t-k}^{pro\_p} + \sum_{k=0}^{K} \beta_{anti\_p,\,k} Bot_{t-k}^{anti\_p} + \sum_{k=0}^{K} \gamma_{anti\_p,k} Human_{t-k}^{anti\_p} + \sum_{k=1}^{K} \lambda_{pro\_p,\,k} Human_{t-k}^{pro\_p} + Seasonal_t + Error_t \qquad ---(1a)$$

$$Human_t^{anti\_p} = \sum_{k=0}^{K} \sigma_{pro\_p,\,k} Bot_{t-k}^{pro\_p} + \sum_{k=0}^{K} \delta_{anti\_p,\,k} Bot_{t-k}^{anti\_p} + \sum_{k=0}^{K} \mu_{pro\_p,\;k} Human_{t-k}^{pro\_p} \sum_{k=1}^{K} \rho_{anti\_p,\,k} Human_{t-k}^{anti\_p} + Seasonal_t + Error_t \qquad ---(1b)$$

where *p* indicates the respective party and *t* denotes the time interval during which the tweets were generated. As observed by previous studies (e.g. Gorodnichenko et al. 2021), the news cycle on Twitter is quite short, around 1 to 2 hours. Thus, the tweets are aggregated over 10-minute intervals to account for the fast-paced twitter traffic and the associated variation. For instance, $Human_t^{pro\_p}$ is the pro-party tweet volume generated by humans during the *t* 10-minute interval.

K = 12, that is, a lag of 12 periods is taken, which amounts to 2 hours. Seasonal is a set of day dummy variables that are included to account for the daily variation in the tweet volumes. Furthermore, the tweet volumes are transformed into logs.[19]

To be transparent, this paper addresses the notion of impact in terms of Granger causality (Granger, 1969). Where for X to Granger cause Y, the past values of X must contain some information to explain Y above and beyond that contained in the past values of Y. It must also be noted that Granger causality only affirms or rejects the presence of an impact, but does not provide its direction. Thus, impulse response functions are employed to further ascertain how the human tweet volume responds to the tweet volume generated by bots. The impulse response functions are also estimated with the within-party specification used for VAR, where the bots' pro- or anti-party tweet volume is considered as the impulse to observe the consequent response of humans in terms of their pro- or anti-party tweet volume.

6. Results

The Granger causality results suggest that the bots' volume of tweets has a significant influence on the tweet volume of humans at the 5% significance level (see table 1). Though the influence is regularly observed for the response of humans to same-inclination bot impulses, the impact is not always significant for across-inclination bot impulses. That is, the impact differs based on the inclination of the tweets generated by both bots and humans. The pro-party/anti-party human tweet volume responds significantly, in terms of higher tweet volume, to the pro-party/against-party bot volume respectively for all the parties. But the influence of the bots on humans is mostly

[19] Dicky-Fuller test was conducted to ascertain the stationarity of the dataset. Furthmore, according to Engle-Granger and Johansen test, no cointegration was found.

not observed, except for the green party and partly for CDU and AfD. That is, pro-green/anti-green bot volume is observed to have a significant impact on anti-green/pro-green human volume respectively. However, for CDU and AfD, the across-party impact is only observed for anti-party tweets generated by bots, which could suggest a greater impetus of the anti-party tweets relative to the pro-party tweets.

[figure 4 goes here]

The influence of across-inclined tweet volumes among humans is relatively more pronounced as compared to that among bots. This is consistent with the findings by Gorodnichenko et al. (2021), about weaker information flows among bots as compared to humans. However, we should be careful with the terminology as the current analysis does not allow for deductions about the information that the public gets exposed to on Twitter. Rather the impact that is observed is for the active tweeting activity in terms of tweeting and retweeting etc.

As discussed in section 5.2, impulse response functions help us assess the size of the impact. For all six parties, the response of human tweet volumes to the same inclination bot volumes is positive, indicating an amplification effect. For CDU (panel A, figure 5), the against-inclined human tweet volume levels out at around 90 to 100 minutes, while the pro-response consists of a comparatively fluctuating pattern. The initial response to the impulse is usually highest, around the first 10 to 30 minutes, as compared to the rest of the gradual trend. Furthermore, the across-inclination responses of humans to bots are mostly not significantly different from zero (confirming the Granger results). Similar trends can be observed for tweet volumes regarding the other parties as well, with slight differences in the relative sizes of the responses and the peaks in the tweet volumes. For example, for AfD, after the initial response in the anti-AfD human tweet volume of 5 percent to the anti-bot volume, it peaks at around 90 minutes at 9 percent (panel B, figure 5). Moreover, the highest immediate response among all the parties is observed for FDP, where a 1 unit increase in the bot anti-FDP and bot pro-FDP volumes gets a 10 to 20 percent response in terms of human anti-FDP and pro-FDP volumes respectively (panel F, figure 5).

[figure 5 goes here]

Though, not the focus of this paper, some bi-directional impact can also be observed from the Granger causality results. This suggests the presence of a feedback effect. That is, the bots' impact on human tweet volume is being fed back into the bot's tweet volume, and so on. The bi-directional causality is only found for the same inclination tweet volumes and not for the across-inclination tweets. In other words, the human tweet volume only influences the bot tweet volume when they are both pro or against a certain party and not when they are on the other side of the ideological divide. Similarly, no feedback effect is found, if any effect at all, amongst the bots' or the humans' own tweeting activity.

7. Discussion and Conclusion

It can be concluded that bots have a significant impact on the human volume of tweets, especially when they share the same inclination toward the relevant party. The absence of a comprehensive influence of the bots across the ideological divide also suggests that their impact is not just random, but that people respond to tweets that are in line with their opinions. These findings are similar to those by Gorodnichenko et al. (2021) in terms of the weaker response of humans to bots' volume from across the ideological divide. However, the comparison must be made within limits, as this paper investigates a political sphere with a multi-party system (and not a binary system). That is, the ideological divide in this paper refers to the inclination in terms of for or against a given party without an inherent implication of support or lack thereof for the other party/ies (as discussed in section 5.1).

Another interesting finding of this paper is the share of tweet volumes. CDU had the highest share of anti-party tweets while AfD had the highest share of pro-party tweets with significant fluctuation near the election day. Similarly, the bots' share of pro-party tweets, of the tweet volume of the respective party, was the highest for AfD as well. This finding is in line with that by Neudert, Kollanyi, and Howard (2017) who found a large amount of AfD-related twitter traffic from a significant share of bots, especially compared to AfD's offline voter support. This also relates to the finding, by Keller and Klinger (2019), of the highest share of active bots among the followers of the top German parties. While this paper examines the impact of bots' presence at the tweets level and not at the level of accounts as by Keller and Klinger (2019), a comparison in terms of AfD-related bots' presence can be drawn between the two studies.

Thus, this paper establishes the presence and the amplifying role of bots in online political communication. The amplifying role of the bots must not be taken as productive, since they are essentially interfering with the information flow and their influence is not neutral. Bots' non-neutrality can be seen from their tweeting activity for and against certain parties, such as the AfD and CDU, and from the size of the impulse responses.

Considering the close election result where SPD took a lead from the incumbent party CDU with only 1.6% of the total vote count, a relatively smaller intrusion or impetus such as that of bots could be responsible. While this paper does not attempt to offer any causal link to the election results, the online political discussion can nonetheless have offline spillovers. Thus, any interference or manipulation in information diffusion and the online discourse cannot be overlooked.

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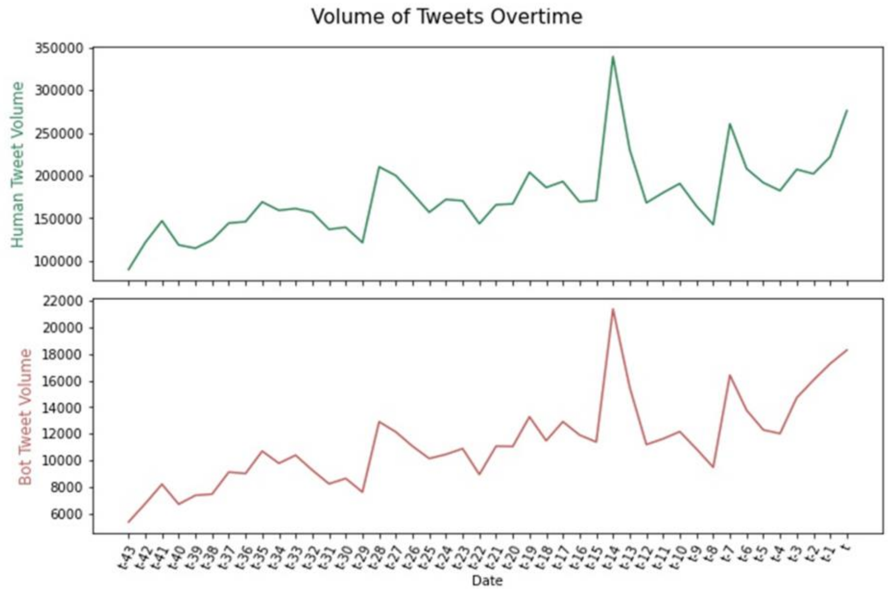
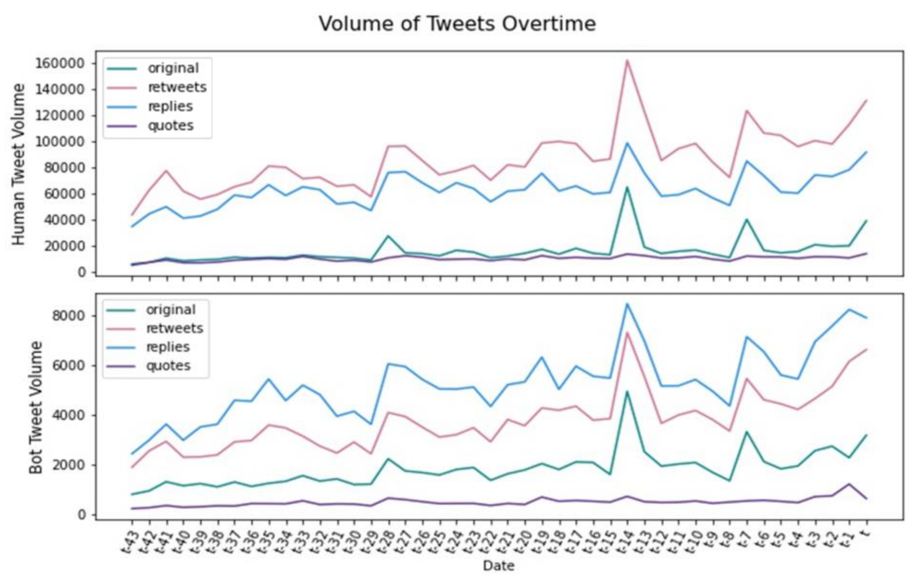
Figures

Figure 1: Dynamics of human and bot tweets



Notes: This figure represents the daily volume of tweets from both human and bot accounts over time. The peaks are similar in both panels, while there are slight differences in volume before and after the peaks and troughs. Especially in the last days leading up to the election day, where the rate of increase in the volume is reasonably different.

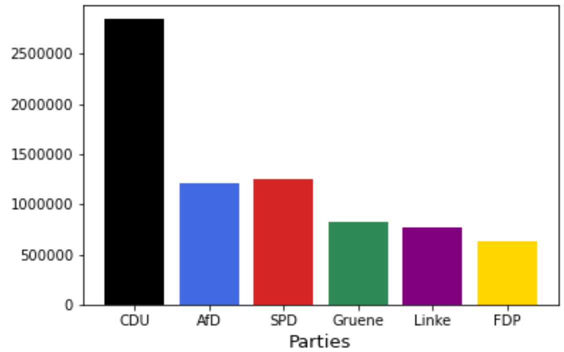
Figure 2: Humans' and Bots' Tweeting Activity According to the Tweet Types



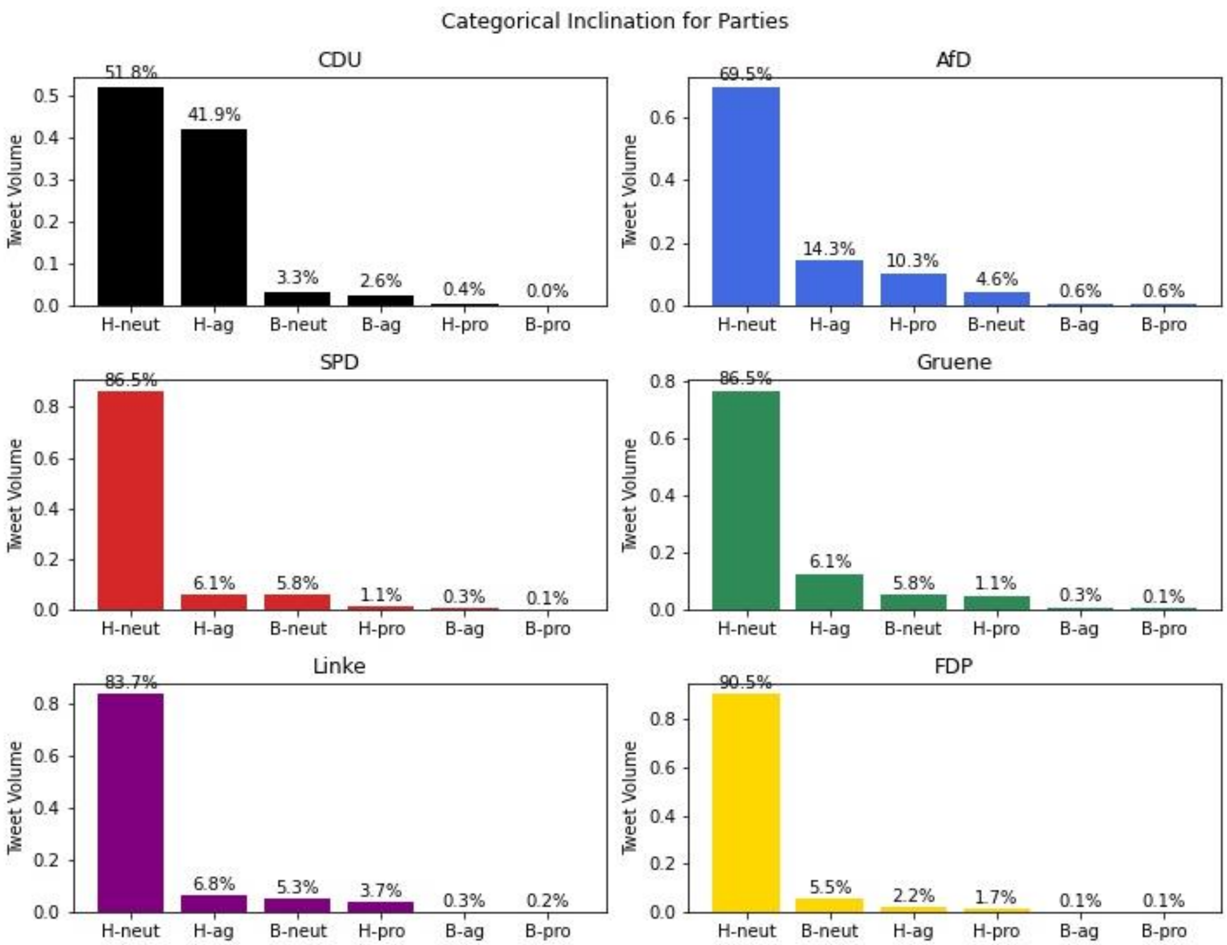
Notes: This figure represents the daily volume of tweets according to the type of tweets over time. The peaks and troughs are mostly similar (except for the last days) for the different types, however, retweets and replies switch their places for bots and humans. That is for bots, replies are higher than retweets throughout the six weeks.

Figure 3: Party-wise tweet volume

Panel A



Panel B



Notes: This figure represents the tweet volumes for each of the six parties. Panel A shows the overall tweet volumes of each of the parties, where CDU has the highest volume, followed by SPD and then AfD. Panel B shows the tweet volumes of the respective parties according to the originators of the tweets and the inclination towards the respective parties in the tweets. H denotes humans and B denotes bots. Similarly, ag, neut, and pro indicate whether the tweets are anti, neutral, or pro for the respective parties.

Figure 4: Visual Representation of Granger Causality Results

Notes: --> indicates uni-directional causality at a 5% confidence level. <--> indicates bi-directional causality at a 5% confidence level.

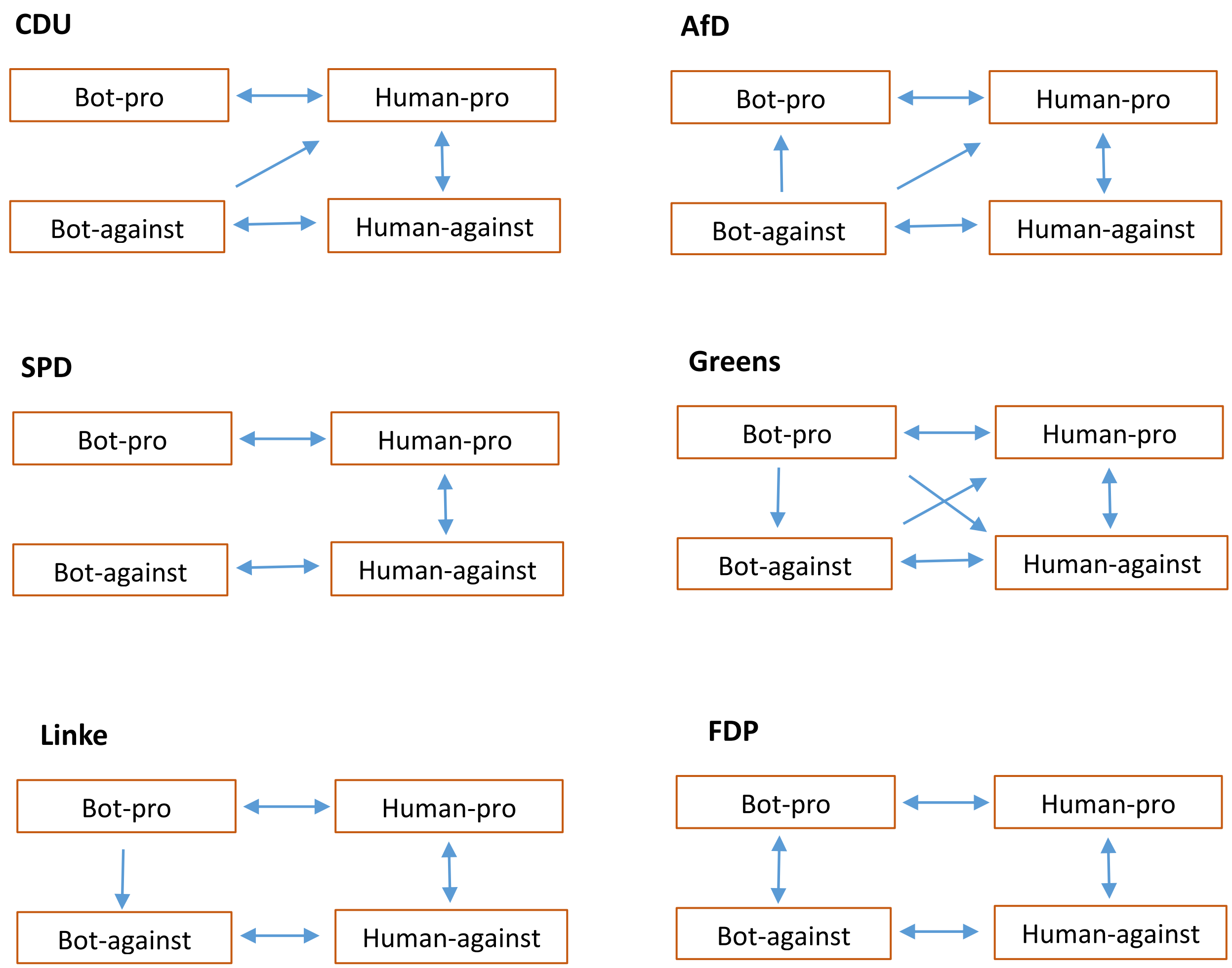
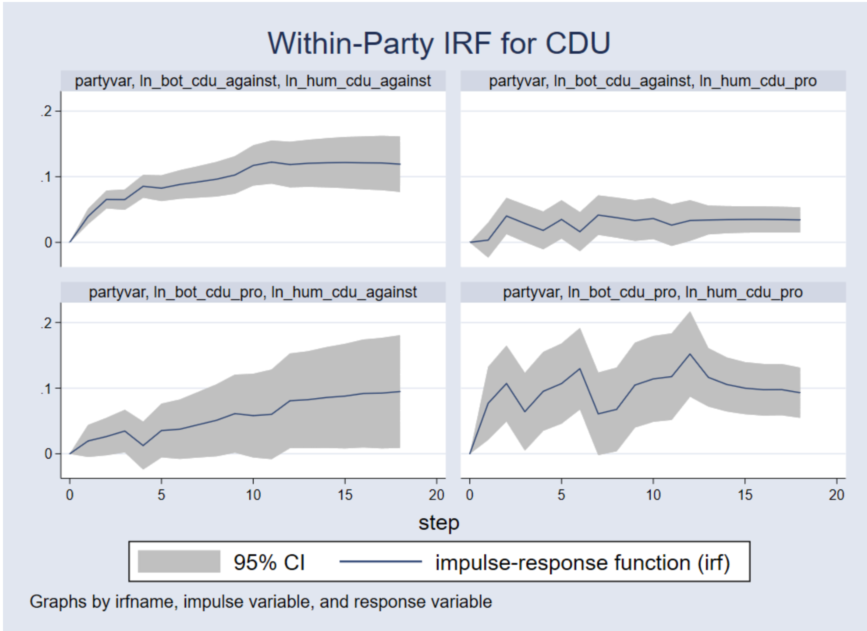
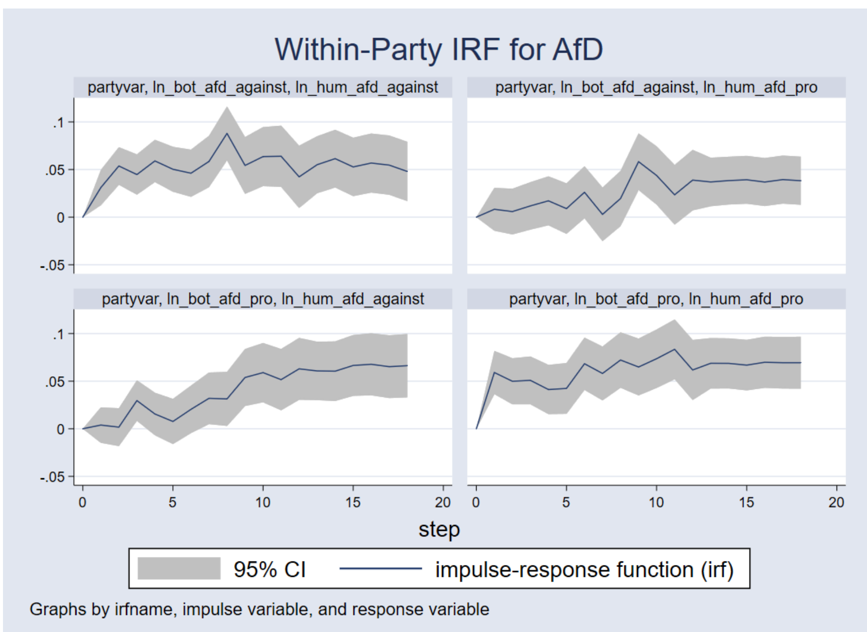


Figure 5: Impulse Response Functions

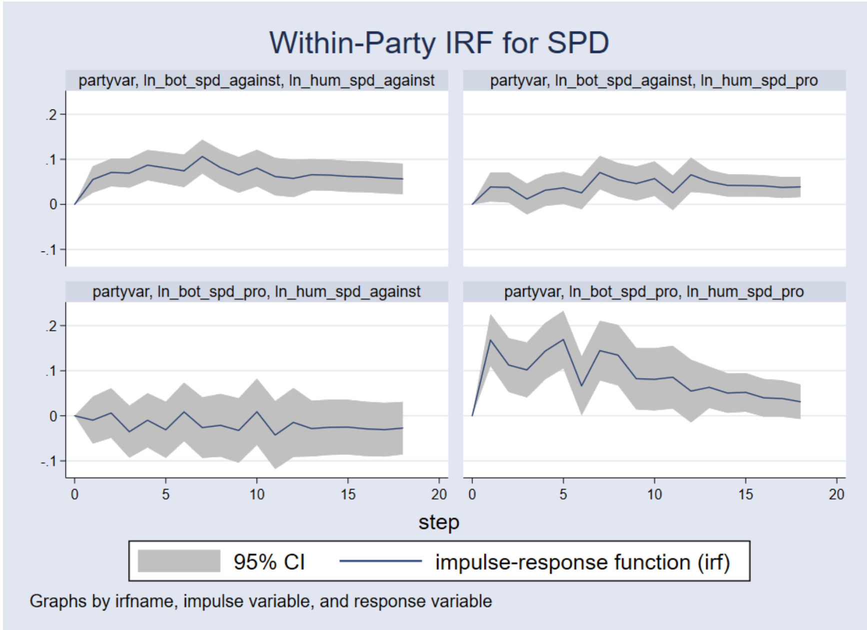
Panel A: Impulse response functions for CDU



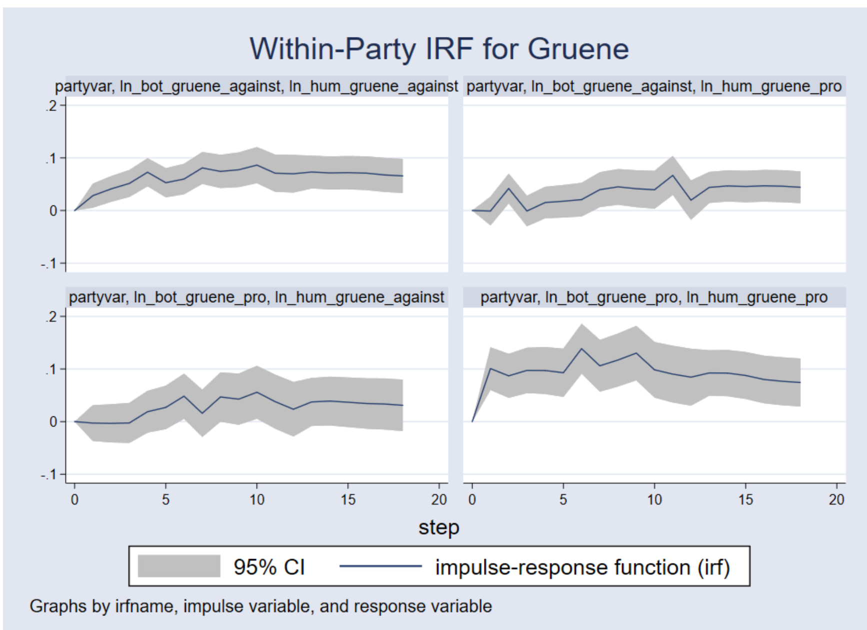
Panel B: Impulse response functions for AfD



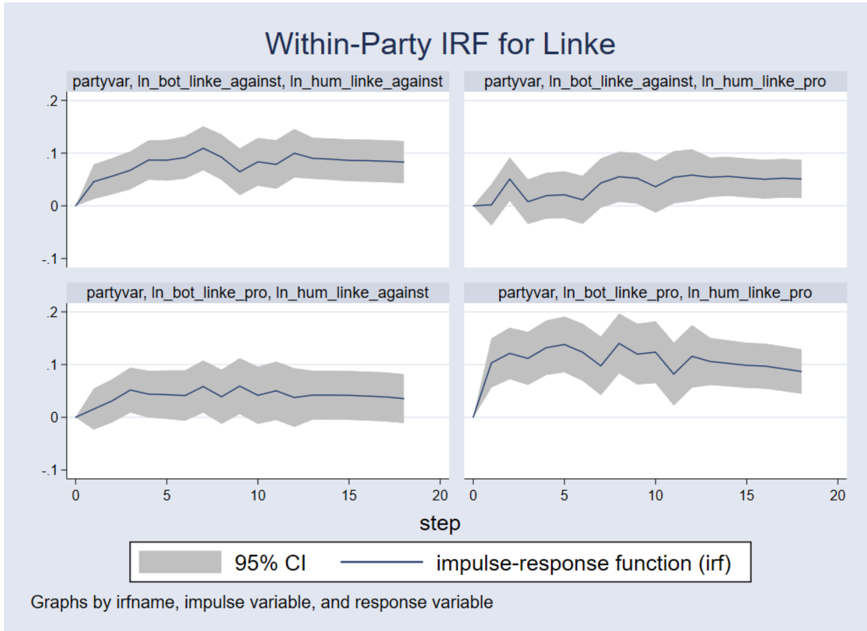
Panel C: Impulse response functions for SPD



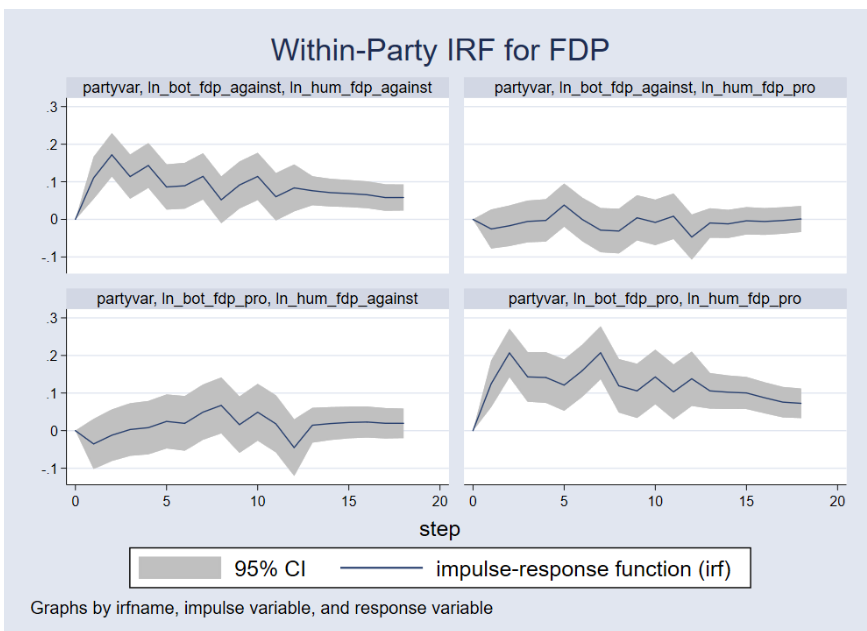
Panel D: Impulse response functions for the Greens



Panel E: Impulse response functions for the Left party



Panel F: Impulse response functions for FDP



Tables

Table 1: Granger Causality Results for Within-Party VAR

CDU	**Dependent Variable**				**AfD**	**Dependent Variable**			
Independent Variable	Hum-pro	Hum-anti	Bot-pro	Bot-anti	**Independent Variable**	Hum-pro	Hum-anti	Bot-pro	Bot-anti
Bot-pro	40.402***	9.881	-	10.299	Bot-pro	62.541***	12.361	-	35.014***
Bot-anti	10.246	119080***	7.316	-	Bot-anti	16.526	59.481***	18.762*	-
Hum-pro	-	37.475***	164.930***	21.960**	Hum-pro	-	229.980***	73.411***	36.642***
Hum-anti	48.343***	-	12.433	912.220***	Hum-anti	327.820***	-	20288*	200.490***
SPD	**Dependent Variable**				**Greune**	**Dependent Variable**			
Independent Variable	Hum-pro	Hum-anti	Bot-pro	Bot-anti	**Independent Variable**	Hum-pro	Hum-anti	Bot-pro	Bot-anti
Bot-pro	69.823***	10.661	-	18.632*	Bot-pro	65.893***	8.274	26.788***	14.682
Bot-anti	19.124*	49.155***	14.639	-	Bot-anti	18.363	44.094***	-	-
Hum-pro	-	48.618***	154.930***	14.657	Hum-pro	-	131.770***	140.170***	29.375***
Hum-anti	97.931***	-	11.151	224.140***	Hum-anti	225.180***	-	25.643**	164.560***
Linke	**Dependent Variable**				**FDP**	**Dependent Variable**			
Independent Variable	Hum-pro	Hum-anti	Bot-pro	Bot-anti	**Independent Variable**	Hum-pro	Hum-anti	Bot-pro	Bot-anti
Bot-pro	59.076***	7.083	-	10.669	Bot-pro	77.719***	10.199	-	31.063***
Bot-anti	9.369	41.689***	26.153**	-	Bot-anti	17.151	63.830***	21.115*	-
Hum-pro	-	55.287***	134.680***	17.686	Hum-pro	-	39.632***	167.840***	12.834
Hum-anti	114.720***	-	16.647	226.430***	Hum-anti	91.283**	-	13.946	105.680***

Notes: This table represents the Granger causality results for each of the six parties. The numbers are the chi2 statistic and *, **, and *** represent significance at 10%, 5%, and 1% confidence levels respectively.