As the Tweet, so the Reply? Gender Bias in Digital Communication with Politicians

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ABSTRACT

This study investigates gender bias in political interactions on digital platforms by considering how politicians present themselves on Twitter and how they are approached by others. Incorporating social identity theory, we use dictionary analyses to detect biases in individual tweets connected to the German federal elections in 2017. Besides sentiment analysis, we introduce a new measure of personal- vs. job-related content in text data, that is validated with structural topic models. Our results indicate that politicians' communication on Twitter is driven by party identity rather than gender. However, we find systematic gender differences in tweets directed at politicians: female politicians are significantly more likely to be reduced to their gender rather than to their profession compared to male politicians.

CCS CONCEPTS

• **General and reference → Empirical studies**; • **Information systems → Social networking sites**.

KEYWORDS

bias, dictionary analysis, gender, topic models, twitter

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1 INTRODUCTION

> "Why do you even care for the #BER [Berlin airport] opening? Because you have to choose your clothes for the opening ceremony??"[1]

This tweet directed at a female German politician resembles an often observed and reported phenomenon in our digital society: digital communication is driven by gender stereotypes rather than job-related content. This, in turn, can lead to bias and discrimination towards female professionals. Building on insights from research on social identities [60, 61] as well as gender biases and gender roles in politics [1, 9, 52], we expect to find gender biased communication on Twitter coming from — but also directed at — politicians. One of the key elements of social identity theory is group membership and categorization: individuals have several identities (i.e. categorizations) assigned by themselves and by others. In politics, a female political candidate can have several identities such as a politician, party member, mother or wife. Based on our own identities and those we assign to others we have different expectations, behave, and engage accordingly with others. Linked to this cognitive process, stereotypes and prejudices can emerge that are related to group categorization [60, 61].

Uncovering gender biased communication on Twitter is especially important since gender stereotypes impact the assessment of politicians and their perceived eligibility for being in office [19, 20, 32, 41]. Little knowledge exists, however, on how gender roles and biases interact in social media communication and how they can be analyzed systematically. Hence, our research extends the current literature by uncovering whether and how politicians are treated differently based on their gender and how this aligns with the presentation of politicians themselves within social networks.

This paper takes up the challenge of identifying latent gender biases in digital communication by analyzing 22.12 million tweets that were collected during the German federal elections in 2017.[2]. After pre-processing and subsetting the data into tweets *by* and tweets *at* politicians, we apply two different dictionaries to the

[1]The original tweet in German can be accessed via: https://twitter.com/KohlmeierSPD/status/772378753032937472?ref_src=twsrc.
[2]The dataset containing the relevant tweet IDs was collected by GESIS [58] and can be accessed via: doi:10.4232/1.12992. All replication materials are available here: https://github.com/arminmertens/ACM_digital_communication

data: (1) We assess the sentiment of each tweet by calculating the *log* ratio of positive to negative words. The dictionary is validated with human coding and has been shown to accurately capture dynamics in political science [47]. (2) We introduce a new measure quantifying gender bias in digital communication on Twitter: a ratio of personal- versus job-related words using LIWC-dictionaries [62]. For personal-related words, the "family", "friends" and "leisure" dictionaries are used while job-related words are captured with the "work" dictionary. The resulting measure can identify whether a tweet is covering more private and personal or professional and job-related communication. We validate the new dictionary using structural topic models [50]. To estimate the effects of gender and political party affiliations on the resulting dictionary measures, different mixed-effects models and predicted values are calculated (see Section 3).

Overall, we find evidence that politicians tend to behave more according to party ideology than their gender identity on Twitter. Additionally, government politicians are more positive than opposition politicians. We also do not find more personal- than job-related tweets by politicians of either sex, suggesting that politicians on Twitter behave more according to their professional identity as party or government members. However, digital communication directed *at* politicians is mainly a function of the politicians' gender, with tweets at female politicians being more personal than tweets at male politicians. Furthermore, tweets directed at politicians are more positive for right-leaning women and left-leaning men. One of the main contributions of this paper is the combination of sentiment analyses with a new personal- versus job-related communication measure uncovering gender bias in the content of tweets. Finally, our findings on substantial differences between tweets directed at politicians and communicated by them provides an empirical test of assumptions of social identity theory on online platforms.

2 RELATED WORK

Politicians and Twitter

Twitter arguably became one of the most important communication arenas in daily political life of many citizens. Initially conceived as a website to share personal status updates, it has now more than 335 million users globally sharing an average of 500 million tweets per day. One distinct characteristic of this social network platform is the presence of not only individuals but also private and public institutions and organizations. Virtually every legislator, political party and candidate in developed democracies has an active Twitter account. Irrespective of their offline identities, they all interact within the same linguistic and symbolic framework. This plethora of data allows social scientists to test a variety of questions.

Theoretical and empirical research. Social science research done on Twitter is diverse both methodologically as well as theoretically. Although reviewing all of Twitter research is beyond the scope of the current article, we review some of the major branches related to our paper. While the vast majority of research focusing on Twitter are purely empirical [35], some studies within political communication and behavior studies are providing a fertile ground for theory-driven research.

Changing the nature of media systems. Addressing the question from the media systems perspective, for instance, Chadwick [16] argues that new media actors, such as Twitter, Facebook and Google, are redefining the power relationships between more traditional institutions. Traditional media is considered to have an important role in keeping public and private institutions accountable to the masses [30]. But with ever more competitive markets, traditional media is becoming both more exclusive and less trusted by the general public. By studying how the gate-keeping role of traditional media outlets is challenged by the newly emerging actors, Chadwick [16] concludes that Western democracies have entered the age of hybrid media systems. Theoretical background to the hybrid media systems research is provided by established areas of communication research. Namely, communication theories on agenda setting [14, 45, 55], framing [27, 34] as well as selective exposure [4, 53].

Political mobilization and protest. Research on mobilization through social networks emerged in the early 2000s with studies focusing on how political actors in the United States mobilized voters through newly emerging personal websites [31, 48]. Due to its geographic focus on the US, the research primarily focused on how emerging technologies are changing the ad-driven nature of political campaigning. Specifically, studies investigate how political actors strategize (try to involve, connect and mobilize citizens) [31] through newly emerging platforms [5] and how campaign communication differs based on gender [18, 54].

Political polarization and opinion formation. Yet another variable through which the effect of Twitter-driven communication is being tested is connected to political polarization and attitude formation [63]. The findings, however, are still inconclusive as to what exactly this technology does to polarization. Liang and Nordin [39] find that high-speed internet access increases online news consumption but has little to no impact on political attitudes. Using quasi-random variation in broadband internet access due to state-level, right-of-way legislation, Lelkes [38] argues that social media platforms exacerbate already existing political tensions. Thus, many argue that the introduction of social networking sites as a prevalent communication tool is contributing to this trend [24]. Empirical evidence of echo-chambers in online communication networks suggests that Internet and social media may aggravate political polarization [2, 17, 59]. That is, research on homogeneous communication networks offline is simply replicated on Internet platforms [6, 25, 29].

On the other hand, Newman et al. [43] find that people who use social networks are exposed to diverse news at a greater rate than people who do not use social networks. This is not surprising if we consider that the majority of ties in any user's personal network are weak — acquaintances, co-workers and distant relatives. Weak ties play a key role in information diffusion on social media [7]. They are important because of their contribution to the spread of novel information which has a higher chance of being ideologically diverse. Barberá [8] provides rigorous empirical evidence of this statement by analyzing how a user following at least one political account becomes slightly more moderate. Finally, Boxell et al. [12] suggest that the relationship between internet and polarization is likely to be complicated and is a function of a particular citizen's level of engagement with news and politics. Lastly, most recent research on Twitter deals with questions of political misinformation and fake news [28, 33, 37]. Actors spreading false information are arguably enabled by the advertising-driven nature of social media networks [3, 37].

Politicians, gender and online platforms

Prior research on gender and politics, more generally, has shown that the activation of stereotypes impacts the evaluation of candidates and voting decisions [9, 52]. Similarly, a study by Aalberg [1] revealed that gender stereotypes lead to changes in the assessment of politicians, their communication and party support. This bias might treat women either as less capable for politics compared to men, or not fit for political office altogether [19, 20, 32, 41]. However, while candidate gender may be a convenient way to make a judgment in an experimental setting, this situation might not be transferable to real voting decisions [21]. Additionally, men and women are attributed with different strengths in politics: men are considered to be more competent in aspects of military and national security, while women ought to be more compassionate [20, 36]. Gender stereotypes might therefore hurt women in some situations, but give them an advantage in others [52].

In the digital age, online platforms such as Twitter, Wikipedia, Facebook and search engines give voters access to information and the possibility to engage with politicians. However, studies found structural gender biases inherent in these platforms. Women are structurally underrepresented on Wikipedia [26, 65] and there are differences in the presence and interaction on Twitter such as women being less retweeted and followed [40].

Twitter is a special case since it allows politicians to communicate with their voters, to campaign and to represent themselves. Likewise, voters have the chance to interact directly with them or to talk about them with a greater audience. Research has, however, repeatedly shown that the tweets with politicians resemble gender stereotypical communication [22, 23, 42, 65].

While politicians change their Twitter communication during campaigning not only their communication style, but also its impact on electoral success, vary with the gender of the politician [42]. For example, research showed that U.S. Senate candidates were more interactive on Twitter when they were women. Both women and men used a more personalized communication style (also termed "feminine communication style"), which can be viewed as a beneficial strategy for mimicking direct (face-to-face) communication [42].

Focusing on gender biased communication with related professionals, research [64] revealed that female political journalists for the U.S. Congress mainly interchange with other women, but men mainly with other men on Twitter. Similarly, Parmelee et al. [46] showed that the behavior of journalists and their interaction on twitter is varying with their gender and generation by using a content analysis of tweets from US political journalists. Their research examined the interactivity by manually categorizing the type of interactivity and the type of users by human coders. Their results suggest that while men were significantly more active in mutual discourse than women, women engaged significantly more in responsive dialogue. Furthermore, their study provided insights into the interaction with politicians. Male journalists engaged more than twice as much as politicians compared to female journalists.

3 METHODS

In order to detect gender differences in the communication with politicians on Twitter, we construct two measures with automated text analyses: first, we shed light on the sentiment of tweets. The sentiment measure creates a log ratio of positive to negative words that have been identified with cross-country validated dictionaries. Second, we introduce a new measure quantifying whether a tweet is covering more personal or professional communication.

Sentiment

We use a sentiment dictionary as proposed by Proksch et al. [47]. It creates a log ratio of positive to negative words and has been shown to accurately capture dynamics in political science, with positive numbers indicating positive sentiment. The dictionary is validated with human coding (for details see [47]). It is based on the Lexicoder Sentiment Dictionary (LSD), which was then translated to German [66].

$$sentiment = log\,(\frac{positive\ words + 0.5}{negative\ words + 0.5}) \tag{1}$$

The LSD tries to achieve both high recall (detecting a wide range of sentiment words), but also high precision (not detecting many false positives). In practice, this is not easy: some words might be associated with positive speech (e.g. military power during wartime) at one point in time and for a certain part of the public, while they are not used positively in other times or by other people. Therefore, the LSD mainly consists of words that are clearly dealing with issues of affection and emotion while avoiding policy-related terms. This approach has been used to study newspaper coverage [56, 57] and legislative debates [47] and we propose to extend this to political use of social media.[3]

Personal- versus job-related communication

Research on gender roles and stereotypes argues and provides evidence that women are generally taken less serious and perceived as less competent compared to men [1, 13]. Therefore, it is reasonable to expect that female politicians receive more personal rather than professional tweets. Following the procedure of Proksch et al. [47] for constructing a sentiment measure, we understand the personal- versus job-related communication measure as a "one-dimensional quantity expressed using a relatively language-specific and possibly institutionally fixed set of lexical resources". A log ratio of personal- versus job-related words is therefore constructed (see table 1)[4] by using a combination of LIWC-dictionaries [62] that relate either to personal and private words ("family", "friends" and "leisure" dictionary) or job-related words ("work" dictionary). LIWC dictionaries have initially been constructed in order to have a new

[3]We expect the dictionary to work adequately at high levels of aggregation. This means that at the level of the individual tweet, a dictionary approach will often have difficulty classifying the tweet as positive or negative, while human coding will typically manage to do so.

[4]The words in table 1 have been translated, original words of the dictionary are in German.

efficient analysis procedure covering psychological processes in the content of writings or talking and it has repeatedly been validated [62].

$$personal\ vs.\ job = log\,(\frac{personal + 0.5}{job + 0.5}) \qquad (2)$$

The resulting measure uncovers personal- relative to role-related information. Thus, a more positive score indicates more personal- compared to job-related tweets, while a more negative one suggests more job- compared to personal-related tweets.

Personal	Job
family (e.g. “children”, “husband”)	work (e.g. “meeting”, “office”, “project”, “colleague”, “negotiate”, “contract”)
friends (e.g. “boyfriend”, “friend”)	
leisure (e.g. ‘beach”, “cinema”)	

Table 1: Constructing dictionaries for "personal" and "job"-related communication

Structural Topic Models

As a complementing measure to dictionary-based analysis, we also look at the results of a more automated text analysis. Namely, we applied topic modelling to our dataset to find if there are additional or contradictory insights to be gained. Topic modelling is one branch of text mining which allows for automatic pattern detection in a large body of unstructured text. The basic goal of topic modelling is to identify topics across documents. Topics consist of specific words and any single document can contain several topics. While there is a variety of different implementations of topic modelling, one of the most frequently used models is the Latent Dirichlet Allocation (LDA) and its various extensions. LDA models define topics as clusters of words that tend to co-occur. Clusters are then compared by a variety of semantic similarity measures. To find these co-occurring clusters, software combs through a textual corpus and compares the occurrence of topics within individual documents to the assignment of clusters in other documents to find the best matches[10, 11].

We chose to use one of the recent LDA-based topic modelling methods called structural topic modelling (STM). The STM’s major advantage is that it allows to vary the distribution of topics as a function of document-level covariates [49, 51]. The inclusion of covariates in the model makes it possible to build and test hypotheses in a regression-like setting. That is, one can to look at covariation between topic prevalence and variables of interest. In this paper, the STM’s ability to incorporate covariates means that we can examine directly our main questions concerning gendered communication. Specifically, we can test if the topics within our corpus are linked to the gender of the political actor who received the tweets. Moreover, the STM allows us to control for other factors that may be related with topic prevalence, such as time, party affiliation and others.

We estimate topic models using the STM package in R [51]. The models are computed with a spectral initialization algorithm which is robust to changes in parameter specification. In practice, this means that irrespective of the seeds set while running the models, one obtains the best results in a consistent manner [44, 49]. Varying the number of topics, we evaluated 61 topics that produced enough information for labelling. After a qualitative labelling of the most-probable words and documents of the models’ topics in the range of 61 topics, we selected 40 topics from the model as the most useful for understanding the degree of gendered communication.

Statistical models

To estimate the effects of gender and political party affiliation on the sentiment of tweets by politicians and the measure for personal- vs. job-related content, respectively, we calculated several mixed-effects regression models. Since tweets sent by the same politician cannot be assumed to be independent of each other, hierarchical models with random effects at the politician level were estimated. We used multiple linear regressions for analyzing the sentiment and personal vs. job-related content of tweets at politicians. The coefficient plots displayed in Section 5 contain predicted values for sentiment and the job-vs.-personal measure with 95% confidence intervals for gender and party.

4 DATA

The twitter data we used in our analysis consists of ∼22.12 million tweets that were collected by Stier et al. [58] in the period from July 5, 2017 until September 30, 2017 — the period around the German federal elections in the same year. Since the provided data only contains the tweet-IDs, we scraped the text of each tweet and relevant adjacent data (screen name, tweet creation date, number of words, number of retweets, favourite count, etc.) by ourselves. After collecting the data, we filtered it according to certain criteria:

(1) Selecting only those tweets where the text column does not have missing values.
(2) Selecting only tweets that were written in German.
(3) Subsetting for tweets that were sent by politicians.
(4) Subsetting another dataset for tweets that were directly sent *to* politicians.

To identify German politicians, we merged the Twitter data with a dataset provided by Castanho Silva and Proksch [15], containing the name, party affiliation and social media handles by most German politicians. After subsetting the data, we received 561,770 tweets which were sent directly to politicians by 86,098 different users and 37,463 tweets which were tweeted by a total of 231 politicians.

Hence, the number of tweets was reduced quite substantially during the process of filtering and subsetting the data. A large number of tweets were simply not directly related to communication with or by politicians, another large chunk of tweets were deleted (by Twitter or the respective users themselves), and some tweets were not related to the German elections but were still acquired during the gathering process.

5 RESULTS

Descriptive statistics

Figure 1 and Figure 2 show the descriptive statistics — i.e. the total number of tweets by party and gender — for all tweets used in the analysis. Several aspects are worth discussing in greater detail. First, looking at Figure 1, it can be observed that politicians from parties in government (CDU/CSU and SPD, indicated by parties displayed above the dashed vertical line) tweet most frequently compared to all opposition parties. This fact, however, might simply be explained by the size of those parties as they are the largest parties in the German political system. More specifically, in conservative parties on the right of the political spectrum (CDU and FDP) tweets by female politicians are extremely rare compared to tweets by male politicians. Second, while in the SPD female politicians also tweet less often than male politicians, the distribution is the opposite for parties more to the left of the political left-right scale: for the Greens and the Left party, female politicians do, in fact, tweet more often the male politicians. One clear particularity is the tweeting behavior of AfD (Alternative for Germany) politicians, the newly introduced far-right party in Germany: there was not a single tweet by a male AfD politician during the German federal elections in 2017 in our sample. Hence, while the ratio of women in the AfD, in general, is very low (less than 11% in the German Bundestag), the debate on social media platforms like Twitter is entirely dominated by female politicians.

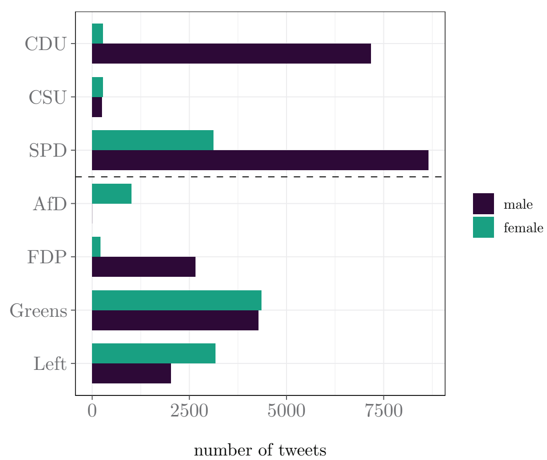

Figure 1: Number of tweets by politicians by party and gender (dashed vertical line indicates government-opposition divide)

When looking at Figure 2, in comparison, most patterns described for tweets *by* politicians can also be found for tweets sent *to* politicians: government parties receive the most tweets compared to opposition parties, although Christian Democrats (CDU) received far less tweets compared to the Social Democratic Party (SPD). Looking at gender differences, for CDU, CSU, SPD and FDP male politicians received almost the entire attention. Only a marginal amount of tweets was sent to female politicians of the respective parties. For the Greens, male politicians also received the majority of tweets. This is especially interesting for the Green Party, as female politicians themselves tweeted slightly more often compared to male politicians (see Figure 1). For the Left Party, female politicians did not only sent out the most tweets, they also received the majority of replies and attention. Lastly, the most striking feature of Figure 2 is the number of tweets sent to AfD politicians. With a comparatively low amount of tweets sent by female AfD politicians (1,016 tweets), the attention those politicians receive is superior to almost all other parties (~120,000 tweets). Only rivalled by the SPD (receiving ~ 152,000 tweets), AfD politicians seem to be very effective in gathering social media attention, which is even more significant, since the attention is focused solely on female politicians.

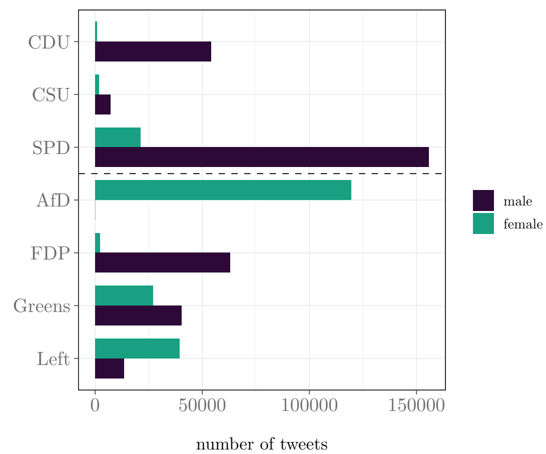

Figure 2: Number of tweets at politicians by party and gender (dashed vertical line indicates government-opposition divide)

Sentiment

Twitter communication by politicians. Figure 3 shows the sentiment of tweets sent out by politicians. Politicians from parties in government (CDU, CSU and SPD) tweet the most positive, irrespective of their gender. Meanwhile, politicians from opposition parties, specifically from the right-wing AfD and the Left, are the most negative. This clearly shows a government-opposition divide of politicians on Twitter, similar to findings of sentiment analysis in parliaments [47]. Gender, on the other hand, does not seem to play a large role for politicians on Twitter. This suggests that politicians act **according to their party identity** on Twitter.

Twitter communication at politicians. In tweets directed at politicians, we can see clear gender differences that seem to be dependent on party. Figure 4 shows that tweets directed at conservative politicians (CDU, CSU) are more positive when the recipient is female and more negative towards male politicians. Meanwhile, male politicians in the SPD and the Left receive more positive tweets than women for these parties. This suggests that politicians are approached **according to their gender identity** by other users on Twitter.

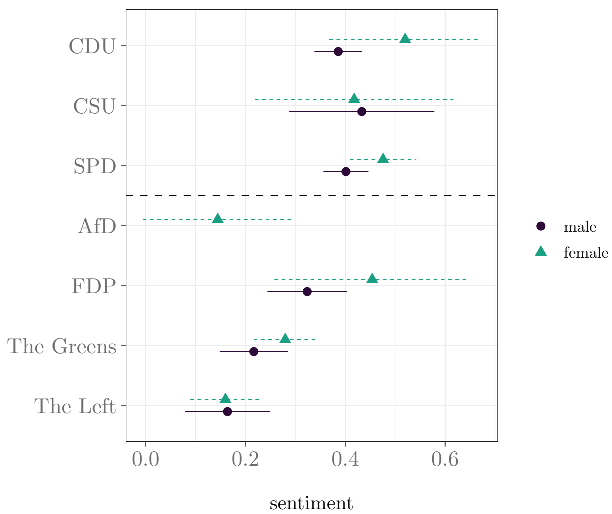

Figure 3: Sentiment in tweets by politicians (dashed vertical line indicates government-opposition divide)

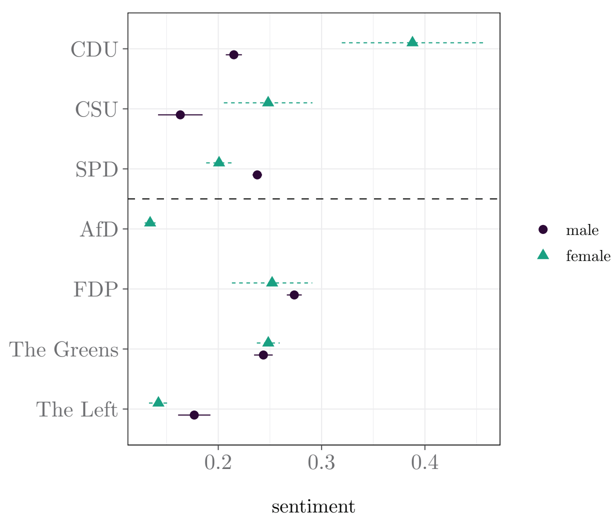

Figure 4: Sentiment in tweets at politicians (dashed vertical line indicates government-opposition divide)

Personal- versus job-related communication

Twitter communication by politicians. The predicted effects of personal- versus job-related communication by politicians (see Figure 5) indicate that their tweets are mainly **a function of their party membership** rather than their gender. One exception, female CDU politicians share the highest amount of personal tweets compared to professional tweets. When comparing politicians being in the government with those being in the opposition, the predicted effects reveal a slightly higher share of personal tweets compared to professional ones for governmental parties. The party AfD has the least personal tweets.

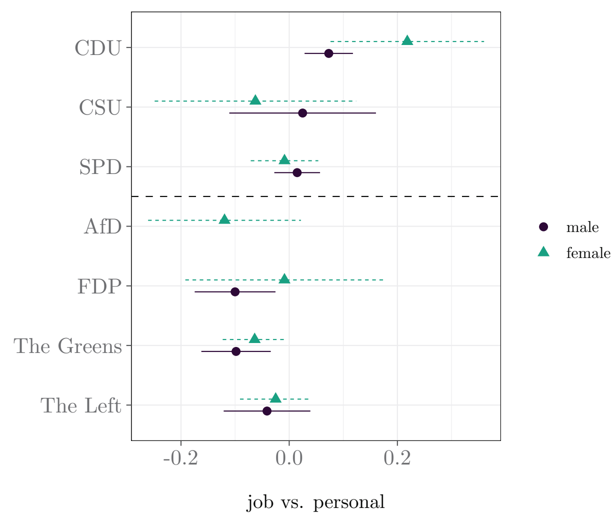

Figure 5: Job vs. personal ratio in tweets by politicians (dashed vertical line indicates government-opposition divide)

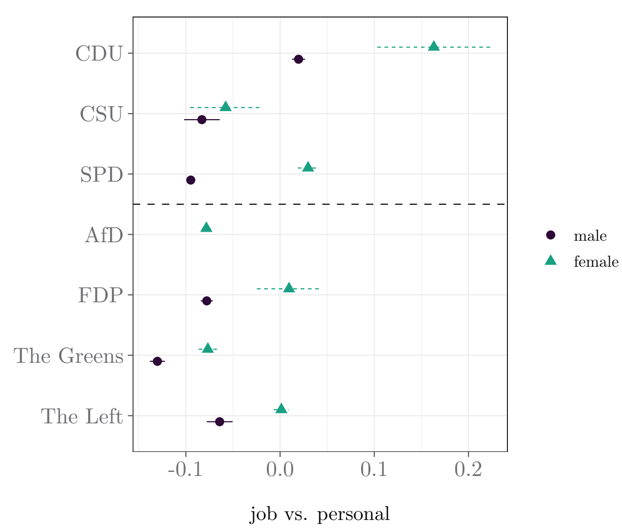

Figure 6: Job vs. personal ratio in tweets at politicians (dashed vertical line indicates government-opposition divide)

Twitter communication at politicians. In contrast, when looking at tweets at politicians the findings look very different. While the personalization of tweets by politicians does not seem to be driven by gender, the predicted effects of personal- versus job-related tweets sent at politicians are mainly **driven by the politicians' gender** (see Figure 6). Specifically, female politicians get more personal than professional tweets. Moreover, the greatest divide between tweets at male and female politicians is observable for politicians belonging to the party CDU, followed by SPD and FDP. Politicians from the Green party receive the lowest amount of personal tweets.

Structural Topic Models

Models derived by using the STM package confirm our findings in the previous section. Namely, we find a significant difference between the type of communication female and male politicians receive on Twitter. Out of 60 topics identified in our Twitter data, only 40 topics were amenable to labelling. That is, we could define — based on the high probability of exclusive words for a given topic — that the topic was dealing with a specific topic (such as democracy, for example). In 65 per cent of cases, there was a significant ($\alpha \leq 0.05$) difference when controlling for gender as a covariate. While covariate effects within the STM models are difficult to interpret substantially, one can study the specific words that are more likely to occur within one topic as opposed to the other.

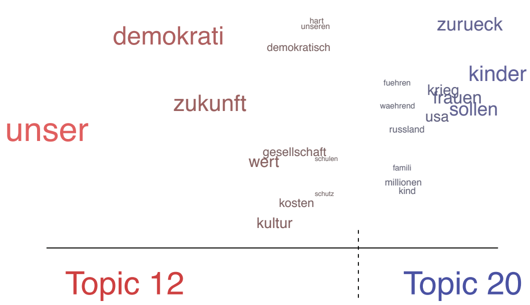

Figure 7: Topic differences based on politicians' gender (from Structural Topic Models)

In Figure 7, we compare two such topics. As can be seen, there are substantial differences within the Tweets received by women (Topic 20) and that by men (Topic 12). Words most frequently occurring within the topic more likely to be received by men (topic 12) are: "our", "democra", "future", "society", "schools", "democratic", schools", "costs, "culture". Women, on the other hand, are more likely - as opposed to men - to receive Topic 20 containing words such as: "children","child", "women", "family", "war" and "should".

Some of the other labelled topics within which we found significant gender differences are presented in Table 2. For topics related to labour markets, labour equality, taxes and pensions, open borders and refugees, there were no gender differences. But for certain areas - especially involving democracy, children and women, foreign affairs, jobs and parenting - women politicians are more likely to be the recipients (as opposed to their male counterparts). In conclusion, substantial review of the vocabulary within topics supports our findings above that there is gendered communication on Twitter, especially when one looks at the types of messages received by political actors.

6 CONCLUSION

Overall, we find evidence that the Twitter communication by politicians can mainly be explained by their party membership rather than their gender. Additionally, the analyses revealed that government politicians tweet more positive than opposition politicians. We find no evidence for gender differences in the amount of personal- compared to job-related tweets by politicians. This suggests that politicians using Twitter behave more according to their professional identity as party or government members and less to their gender identity with the aligned stereotypes. However, we find systematic gender differences in digital communication directed *at* politicians, with tweets at female politicians being more personal than tweets at male politicians. Moreover, tweets at politicians are more positive for right-leaning women and left-leaning men.

The main contribution of this work is the combination of sentiment analysis with a new personal- versus job-related communication measure uncovering gender bias in the content of tweets. This research may also provide valuable insights for adjacent scientific fields such as gender biases on online platforms in general, measurement of social group discrimination and communication biases towards female professionals.

A somewhat related question that could be raised with this study concerns the existence of various combinations of sentiment and personalization in tweets and the effects on individuals: Under which circumstances are personalized or professional tweets negatively, positively or neutrally formulated — and does this vary significantly with the gender and party of the politician? How do the different combinations of sentiment and personalization affect voters? When dissecting tweets sent to politicians, the gender and ideology of the sender should be taken into account: Are negative tweets towards female left-leaning politicians sent by their own party supporters or are supporters of right-leaning parties targeting left-leaning women and vice versa?

No Gender Differences	Significant Gender Differences
Endangered labour markets; Elections; Taxes and pensions; Labour equality; Merkel, open borders and refugees	Children and women; Jobs and parenting, working parents; Anti-fascist movement; Greens and Environmental policy; Rights; Democracy and future; Germany, Turkey and the EU; Foreign affairs; Religion and politics.

Table 2: Gender differences in Structural Topic Models

In addition, other factors such as seniority or ministry position may also be crucial for explaining the tweeting behavior of politicians. Future research is needed to investigate their effects and their moderating role. Moreover, this line of research could benefit from including previously unavailable measures of the political orientation and gender of twitter users into the analysis. Finally, using a similar approach, research should explore whether other societal biases are also reflected on online platforms, such as Twitter, and how these biases influence political behavior.

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