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The Role of Gender in Hate Speech Targeting Politicians: Evidence from Finnish Twitter

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Abstract
This study uses a manually classified tweet sample for examining hate speech targeting the ministers of the government of Finland. We use logistic regressions to investigate the distribution of hate speech by gender, age, party leadership, visibility, and political party, with a special focus on gender. Additionally, we divide minister portfolios into masculine, neutral, and feminine positions and examine whether a minister's gender affects the likelihood of being targeted. Our results suggest that male and female ministers are equally likely, on average, to be targeted by hate speech. However, this relation is nuanced. First, for male ministers, visibility increases the frequency of hate speech. For female ministers, the result is the opposite. Moreover, the results suggest that women in masculine positions are more likely to face hate speech. In addition, men are targeted by hate speech less when they are holding a masculine minister portfolio. This suggests that gender roles affect hate speech.

Keywords Hate speech · Cyberbullying · E-democracy · Online communication · Twitter

Introduction

Twitter and other social media allow politicians to express their views to a large public. In addition, social media can be used for directly interacting with different interest groups, including a politician's voters. As a downside of this, social media makes targeting politicians with hate speech effortless. For example, Theocharis et al. (2016) argued that politicians are a prime target of online harassment. In this study, we examine hate speech targeting the ministers of Marin's cabinet, i.e., the government of Finland from 2019 to 2023. Our main objective is to examine the

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distribution of hate speech by the ministers' gender, age, political party, visibility, and leadership. Our main focus is on the role of gender in political hate speech.

Marin's cabinet offers an intriguing research setting because women are well represented in it. First, half of the ministers are women. Second, the prime minister is a woman. Since the prime minister is the head of the government, she is by far the most important and visible minister in Finland. Third, many of the other key ministers are women, such as the minister of finance and the minister of the interior. Fourth, five of the female ministers are also party leaders. They lead all the five parties represented in the cabinet. Furthermore, these five parties had almost 60% of the seats in the Finnish Parliament from 2019 to 2023. Hence, female politicians possessed a substantial amount of political power in Finland over the period from 2019 to 2023. For these reasons, Marin's cabinet provides an excellent opportunity to examine the role of gender in hate speech. Hence, this study contributes to the literature by examining hate speech in a political setting where women are both well represented and hold political power.

Theoretically, this study contributes to the growing literature on gendered political violence. For example, Håkansson (2023) and Bardall et al. (2020) have previously addressed similar issues. A common assumption in hate speech studies is that women are more frequently targeted by hate speech than men. Krook (2017) reviewed the reasons why women may be targeted more than men by political violence. Briefly, acts of violence may reflect attempts to deter women's electoral participation, reinforce gender norms, and restrict women's contribution to politics. Krook argued that there is growing evidence suggesting that female politicians face more difficulties than their male counterparts. These are instigated by those who oppose women's participation. She suggests that all efforts to harm, harass, and intimidate women are a threat to democracy. According to the Inter-Parliamentary Union (2016), the most common form of violence targeting members of parliament (MPs) is psychological violence. Globally, more than 80% of female MPs were reported to have been subjected to psychological violence. Krook and Sanín (2020) pointed out that psychological violence may be carried out in person or online.

Rudman and Phelan (2008) argued that women are perceived to be less competent, ambitious, and competitive than men. As a result, they may be overlooked for leadership positions unless they present themselves as atypical women. Likewise, Eagly and Karau (2002) suggested that attitudes toward female leaders and candidates are less positive than attitudes toward their male counterparts. Moreover, it is more difficult for women to become leaders and achieve success in leadership roles. This is because women face prejudices due to the perceived incongruity between the female gender role and the leadership role.

Consistent with this, Kenny (2013) posited that political parties may select their candidates based on gendered criteria. In addition, gender norms may even result in women self-selecting themselves out of the process. Thus, gender norms shape both the supply and demand of female candidates. Franceschet (2017) argued that in the absence of formal rules constraining participation, these informal rules may result in gendered patterns in politics. Eriksson and Håkansson (2023) concluded that these gender biases, including masculine leadership ideals, can prevail even if there is a large number of female leaders.

Beltran et al. (2021) suggested that gendered communication from citizens to politicians may be driven by, e.g., different treatment of genders. In line with this, many studies have suggested that female politicians face more uncivil and hateful content than their male colleagues. However, this relationship is not always straightforward. For example, Rheault et al. (2019) showed, using a large sample of tweets sent to U.S. and Canadian politicians, that men are more frequently targeted by hate speech than women. Nonetheless, this result reverses when a politician's visibility increases. As a result, female politicians face more incivility than male politicians when they occupy highly visible positions, where they are perceived to be breaking the glass ceiling.

Erikson et al. (2021) showed that Swedish male and female MPs had no difference in the frequency of abusive messages. These authors used a dataset based on a survey of self-reported data. However, Håkansson (2021) suggested that women are targeted more than men by political psychological violence when they are powerful and visible. Men were overrepresented as targets of physical violence. She studied survey data collected from Swedish local-level politicians. Further, Mechkova and Wilson (2021) show that female candidates in the 2018 U.S. elections were more likely to be the subject of abusive tweets. Moreover, Herrick and Thomas (2022), using a survey of U.S. state senators, showed that women with higher levels of power, i.e., party and committee leaders, were more likely than other women to experience psychological abuse, sexualized abuse, and violence.

Southern and Harmer (2021) showed that male MPs are more often targeted by hate speech than their female counterparts. Nonetheless, female politicians were more likely to receive at least one uncivil message. These authors used a manually classified tweet sample consisting of tweets sent to British politicians. Even if men received more uncivil messages, women received more stereotyping tweets and tweets questioning their position. Similarly, Ward and McLoughlin (2020) suggested that male MPs attracted more abuse in their sample containing tweets sent to British MPs. These authors argue that while some abuse is targeted and gendered, the biggest proportion of abuse follows a reactive response to political discussions. These authors used a semi-automated process for identifying abusive tweets.

Esposito and Breeze (2022) used a sample of tweets sent to 10 British politicians to examine both the quantitative and qualitative nature of hate speech targeting politicians. These authors found no statistically significant differences between tweets referring to male and female politicians in several semantic fields, such as appearance and intelligence. Despite this, the content of the abusive messages showed how certain stereotypes concerning female behavior are still operative in UK politics. Furthermore, Bauschke and Jäckle (2023) showed that German female mayors did not exhibit a higher risk of experiencing hate speech than their male counterparts. Likewise, age and political party did not affect the likelihood of being targeted by hate speech. Bauschke and Jäckle (2023) concluded that there is no clear type of victim of hate speech in the sample of mayors.

Previously, a handful of studies have examined the distribution of hate speech by gender in Finland. Van Sant et al. (2021) used a machine learning algorithm to show that the female ministers of Marin's cabinet experience more hate speech than the male ministers. In addition to the higher frequency, hate speech targeting the female ministers

was gendered and sexualized. Likewise, Knuutila et al. (2019) used a machine learning algorithm to investigate the distribution of hate speech among Finnish male and female politicians. As opposed to the study of Van Sant et al. (2021), their results suggested that men are targeted by hate speech more than women.

Against this background, we use logistic regressions for testing the following hypotheses: (i) female ministers are more frequently targeted by hate speech than male ministers; (ii) the prime minister receives more hateful tweets than other ministers because she is a woman possessing political power; (iii) five female ministers in Marin's cabinet are also party leaders, so they suffer more from hateful tweets than other ministers, as Herrick and Thomas (2022) and Håkansson (2021) showed that female politicians with power face resistance; and (iv) visibility increases hate speech targeting female ministers. We use the number of Twitter followers as the variable to measure a minister's visibility. This is similar to Rheault et al.'s (2019) work.

Furthermore, following the classification by Krook and O'Brien (2012), we divide the minister portfolios into masculine, neutral, and feminine minister portfolios. For example, the minister of defence and the minister of finance are considered masculine minister portfolios. In comparison, the minister of education and the minister of social services and family affairs are feminine minister portfolios. Using logistic regressions, we examine whether men having a feminine minister portfolio are targeted more frequently by hate speech than other ministers. Similarly, we investigate whether women having a masculine minister portfolio suffer more from hate speech than other ministers. Our objective is to investigate whether traditional gender roles affect the likelihood of being targeted by hate speech. Previously, Goddard (2019) and Curtin et al. (2023) used the typology of Krook and O'Brien (2012) for examining minister portfolio allocation[1]. As for Krook and O'Brien (2012), they used this typology in calculating a score measuring government gender parity in 117 countries, including Finland. This is the first study that uses this typology for studying hate speech.

Last, we break the hateful tweets down into two categories: stereotyping tweets and sexualized tweets. The former is motivated by Southern and Harmer (2021), who argue that women are more often targeted by stereotyping tweets. Moreover, these authors suggest that stereotyping tweets targeting male politicians are more often political, e.g., relating to a politician's party. As for female politicians, stereotyping tweets often relate to their gender. Likewise, Saluja and Thilaka (2021) suggested that a female politician's leadership qualities are often related with aspects of her gender identity. Accordingly, we divide stereotyping tweets into gendered and political stereotyping tweets. Furthermore, Van Sant et al. (2021), Bjarnegård (2023), Bjarnegård et al. (2022), and Erikson et al. (2021) suggested that hate speech targeting female politicians is often sexualized. Hence, we create a separate category for sexualized abusive messages.

This study is organized as follows: after the introduction, we briefly discuss Marin's cabinet and the Finnish Parliament. It is followed by our definition of hate speech, and we also explain the process of manual classification. Next, we discuss

[1] Goddard (2019) examined portfolio allocation in 29 European countries, including Finland, and Curtin et al. (2023) used data from Canada, Australia, and New Zealand.

why Twitter is our data source. This is followed by the descriptions of the tweet sample and the empirical strategy. After that, we present the results. Last, there are our conclusions.

Marin's Cabinet of Ministers and the Finnish Parliament

Prime Minister Sanna Marin gained international fame when she was appointed as the world's youngest serving head of a country's government in December 2019. Moreover, five of the female ministers, including Sanna Marin, were leaders of their political parties. In an interview (Reuters, 2022), she expressed that she and her female colleagues had been targeted by hate speech for their gender and appearance.

Women's participation in politics in Finland was historically and internationally high from 2019 to 2023[2]. The share of women MPs elected in the 2019 parliamentary elections was 47% (Parliament of Finland, 2023a). Compared to this, the share of women in the House of Commons of the UK is 35% in 2023 (Uberoi & Mansfield, 2023) and in the 118th U.S. Congress is 28% (Pew Research Center, 2023)[3]. However, there are large differences between the political parties in the Finnish Parliament. For example, the Greens was a female-dominated party because 85% of its MPs were women. In contrast, 71% of MPs of the Finns party were men (Parliament of Finland, 2023b).

Prime Minister Sanna Marin was appointed as the prime minister after the previous prime minister Antti Rinne had to resign after a scandalous postal strike in December 2019. Since she was only 34 years old at the time of appointment, Sanna Marin was a relatively young prime minister. Besides her, several other female ministers in the cabinet were in their 30s[4]. There were 19 minister portfolios in Marin's cabinet. The sample period in this study is from April 2021 to August 2021. In total, there were 22 ministers in the cabinet during this period because some ministers temporarily left the cabinet for personal reasons. Hence, new ministers were appointed to these positions. These 22 ministers were equally divided into male and female ministers. Hence, having a female prime minister did not result in fewer women in the cabinet as suggested by O'Brien et al. (2015). Furthermore, two of the ministers are Swedish-speaking Finns, while the Minister of Foreign Affairs, Pekka Haavisto, publicly identifies as gay. Other than these three, there are no minorities in Marin's cabinet.

The political parties forming the cabinet were the Social Democratic Party, the Greens, the Left Alliance, the Centre Party, and the Swedish People's Party of

[2] According to the Inter-Parliamentary Union (2023), Finland ranks 15th in terms of female parliamentary representation. The highest share of women in the national parliament is in Rwanda (61.3%).

[3] Teele et al. (2018) argued that American elites and voters prefer candidates with traditional household profiles. These authors conclude that women are likely to remain underrepresented in U.S. politics as long as these social familial commitments cut against the demands of a political career.

[4] Kroeber and Hüffelmann (2022) showed using a sample of 29 European countries from 1990 to 2018 that it takes women more time to enter the cabinet to receive responsibility for a prestigious portfolio than men. However, in Marin's cabinet, the prime minister, the minister of the interior, and the minister of finance are all women in their 30s.

Finland. The last mainly represents the Swedish-speaking Finns. As for the Social Democratic Party and the Left Alliance, they are leftist parties. The Centre Party is a right-wing party that has traditionally been especially popular in the rural areas of Finland. Finally, the Greens is an environmental party.

There were two major parties in the opposition. One of them was the right-wing party, National Coalition, which is often the most supported party in Finnish cities. The second major party in the opposition was the nationalist Finns Party. Besides them, the opposition included the religious Christian Democratic Party. In addition, there were two one-man parties in the Finnish Parliament during the sample period: *Liike Nyt* (Movement Now) and *Valta kuuluu kansalle* (The Power Belongs to the People). The latter was formed after the MP was forced to resign from the Finns party after he published a hateful tweet.

There are 200 seats in the Finnish Parliament. From 2019 to 2023, the two largest parties were the Social Democratic Party (40 seats) and the Finns Party (38 seats). The National Coalition had 37 seats, the Centre Party had 31 seats, the Greens had 20 seats, and the Left Alliance had 16 seats. The Swedish People's Party had 10 seats, i.e., 5% of all the seats, which is approximately the share of the Swedish-speaking Finns of the total population. In addition, the Christian Democrats had five seats, and there were two one-man parties with one seat each. Together, these sum up to 199 seats. The 200th seat is that of the Speaker who directs parliamentary work. He or she is not allowed to vote or participate in the conversation.

Being a politician in Finland is safe because at least visible physical political violence is relatively rare. The latest political assassination was that of the Minister of the Interior, Heikki Ritavuori, in 1922. However, there was an assassination attempt on a male municipal politician, Pekka Kataja, in 2020. As of today, the motive is unknown. Moreover, a Member of the European Parliament, Teuvo Hakkarainen, was stabbed with a knife in a violent act that likely was not politically motivated in Honduras in 2021. Generally, even if the relative number of violent deaths in Finland is internationally low, men are disproportionately overrepresented as victims. Depending on the decade and year, 70–90% of those violently killed are men in Finland (Lehti, 2020).

Using Twitter for Studying Hate Speech

It is important to address the question of the suitability of Twitter data for hate speech research. First, all the ministers in Marin's cabinet had a Twitter account. In addition, they actively tweeted during the sample period. As a result, all the ministers are included in the tweet sample. Moreover, Finnish ministers use Twitter for communication and political announcements. Their tweets may reach larger audiences outside Twitter because Finnish news agencies often cite ministers' tweets in their news (e.g., YLE, 2021). The downside of Twitter is that it is not as popular as some other social media. In 2020, 13% of Finns used Twitter (Statistics of Finland, 2021a). Hence, it was a much less popular social media than Facebook that was used by 58% of Finns. Today, Twitter is the most studied social media platform in hate

speech research because of the easy availability of data (Matamoros-Fernández & Farkas, 2021)[5].

Twitter is a public medium where messages are typically visible to everyone. One can also send private messages on Twitter, but these messages are not included in this sample. This may lead to biased results. Nonetheless, previous studies have shown that abusive behavior is common in public social media. For instance, Knuutila et al. (2019) suggested that municipal policymakers were targeted by hate speech most often on Facebook. According to Korhonen et al. (2016), minority groups experienced more hate speech on Facebook than on any other social media platform. However, the most common location for hate speech and harassment was a public space. There is not much information on the relative amount of hate speech on different social media platforms. Kettunen and Mari-Sanna (2021) used a machine learning algorithm to show that one message in every 100,000 messages on Finnish public Facebook was hateful, while 0.14% of tweets were hateful on Twitter.

Tweet Sample

The sample consists of tweets that were sent to the ministers of Marin's cabinet. Therefore, not all the political parties in the Finnish Parliament are included. The tweet sample was collected continuously over time using the Twitter streaming API, and Python was used for the programming. In total, the sample contains 10,046 tweets. The sample period is from 7 April 2021 to 20 August 2021, and the number of ministers was 22 during the sample period. In 2021, Twitter had become an important medium for the Finnish politicians. Resulting from this, all the sample ministers had a Twitter profile. Furthermore, Sanna Marin had already been the prime minister for more than a year during our sample period because the former prime minister Antti Rinne resigned in December 2019. Since retweeting is an important feature of Twitter, the sample contains retweets. The total number of tweeting accounts in the sample is 4258. Hence, there were, on average, about 2.4 tweets per account.

The sample tweets are all in the Finnish language. Thus, Swedish, Norwegian, and English tweets in the threads of the ministers of the Swedish People's Party were excluded from the sample. This was done to ensure high precision in the classification. Nonetheless, we consider this as a limitation especially because the two Swedish-speaking ministers are the only ethnic minority in the sample. Furthermore, the sample is very small for some of the ministers. For instance, the Minister for Nordic Cooperation and Equality, Thomas Blomqvist, only has ten observations in the sample. In comparison, Prime Minister Sanna Marin has 1195 observations. Thomas Blomqvist tweeted actively during the sample period, but his tweets did not generate discussion.

All the tweets were classified into non-hateful and hateful tweets manually, i.e., by reading. Furthermore, the tweets were read and coded by a single author. Manual classification has been previously used by, e.g., Åkerlund (2020) and Southern and

[5] For a review of Twitter research, see Antonakaki et al. (2021).

Harmer (2021). Briefly, a tweet is hateful when it is a hostile and offending tweet that does not relate to the minister's professional role. If a tweet contained harsh language but targeted either the minister's professional role, announcement, or politics, it was typically classified as a non-hateful message. This is where manual classification substantially differs from automated classification because an algorithm cannot recognize whether the content concerns a politician's professional role.

For the classification, we created a dummy variable that gets the value of 1 if the tweet is hateful. If the tweet is non-hateful, the value is 0. This variable is used as the dependent variable in the logistic regressions. Previous studies by Southern and Harmer (2021) and Rheault et al. (2019) used similar regressions for examining hate speech. Logistic regressions allow for examining how a variable affects the likelihood of hate speech when the effects of other variables are accounted for.

Definition of Hate Speech and Manual Classification

Defining hate speech is a challenging task. We rely on the definition used by Kettunen and Mari-Sanna (2021). Accordingly, expressions that are derogatory, humiliating, threatening, hostile, offensive, or dehumanizing are defined as hate speech. Second, they can relate to personal characteristics or stigmatize a specific group or generalize. Third, the hateful content may target a professional group without relating to its professional role. Besides these, Kettunen and Mari-Sanna (2021) separately categorized all other expressions that can be interpreted to be hostile or advocate discrimination and violence.

As Vidgen and Derczynski (2021) argued, abuse is intersubjective. In our case, all the tweets were analyzed by a single researcher. Despite this, there is subjectivity in our annotation because the difference between a hateful and a non-hateful message is not always clear. In addition, classifying messages is not only about drawing the line between hateful and non-hateful content. For example, the collapse of Afghanistan and the return of the Taliban occurred during the sample period. There was plenty of conversation concerning these events on Finnish Twitter. When classifying tweets into hateful and non-hateful content, one must decide what type of language can be used when discussing the Taliban. Some might opine that the group can be called terrorists without being hateful.

Additionally, there are challenges in classifying hate speech targeting specific persons. For instance, accusing a minister of corruption is not rare. While it is typically hostile content, there could be difficulty in classifying it as non-hateful or hateful content. For example, Minister of Defence, Antti Kaikkonen, was sentenced for misuse of a position of trust (*luottamusaseman väärinkäyttö*) in 2013. No one accuses him of corruption in this sample, but one could ask whether his sentence is a sufficient reason for accusing him of corruption.

Many studies have used automated methodologies for detecting hate speech. The majority of them result in a binary variable indicating hateful messages. For example, Lingiardi et al. (2020) used a lexicon-based approach, and Gorrell et al. (2020) used a rule-based approach for detecting hateful content. Studies such as by Vidgen

and Yasseri (2020) and Burnap and Williams (2016) used machine learning techniques for hate speech detection[6].

Manual classification improves precision for several reasons. The most important reason is that an artificial intelligence (AI) model is at most as accurate as a human coder. It does not have an information advantage, as using it requires a manually classified sample of tweets, which serves as the learning sample. Thus, an AI model learns from a manually coded sample. In addition, manual classification does not rely on a lexicon of abusive terms that risks the exclusion of part of the hateful content. Moreover, Kwarteng et al. (2022) argued that automated detection tools lack sensitivity to context. Classifying messages by reading overcomes this problem because the context is known.

We used a definition similar to the one presented above. Briefly, this definition defines hostile and abusive content that is unrelated to a minister's professional role as hateful content. We have classified all the tweets that offend or insult, such as accusations of corruption and lying, name-calling, and accusations of treason. Furthermore, hate speech contains all forms of racism and sexism. Moreover, even indirect threats of violence are classified as hate speech. Likewise, suggesting committing suicide and wishing a minister to die are classified as hate speech. Criticizing a minister's appearance is classified as hate speech because it does not relate to their professional role.

It is noteworthy to mention that this definition of hate speech is much wider than the one given by the Council of Europe (2016), which defines hate speech as racism, xenophobia, antisemitism, and similar types of intolerance. These types of hate speech were not very common in our sample because minorities are not well represented in Marin's cabinet. Very often, hateful tweets related to the ministers themselves; that is, they were person-directed (Vidgen & Derczynski, 2021). For example, the tweet "*Sinä olet ääliö ja äänestäjäsi ovat imbesillejä.*" (You are a moron and your voters are imbeciles.) relates to the minister. If hate speech was defined according to the Council of Europe (2016), this message would not be hate speech. Hateful tweets also included group-specific abuse. For instance, the tweet "*Yritä nyt erota. Teidän akkalauman tekemisestä ei tule yhtään mitään.*" (Try to resign. You bunch of bitches cannot do anything.) is a misogynist message.

Sometimes, a minister's decisions and opinions ignited harsh criticism. However, we classified such messages as non-hateful if they related to the minister's professional role[7]. For example, "*Paskin ministeri ikinä!*" (The shittiest minister ever!) is a rude and offensive tweet. Despite this, it targets the minister's professional role. Hence, it was classified as a non-hateful message. Similarly, the tweet "*Olipa Jari paska tviitti. Vittuun ne verkot sieltä, vai pitääkö hakea itse?*" (Jari, what a shitty tweet. Get those nets the hell out of there, or do I have to get them myself?) was classified as a non-hateful message. The sender was worried about fishing-related deaths of the near-extinct Saimaa ringed seals. Thus, we classified it as a non-hateful

[6] See Fortuna and Nunes (2018) for a review of the automatic detection of hate speech in text.

[7] The number of such tweets was low, at 5. Classifying these messages as hateful did not change any of the results.

message. This is different from Rheault et al. (2019), who coded a message as uncivil if it contained swear words.

We created separate categories for stereotyping and sexualized hateful tweets. Furthermore, we divide stereotyping tweets into gendered, political, and immigration-related stereotyping tweets. Kanahara (2006) reviewed the various definitions used in the literature on stereotypes and proposed the definition of "a belief about a group of individuals." According to Kanahara (2006), the concepts of belief and group are the most important in describing stereotypes. Hence, we classified a hateful tweet as stereotyping if it represented someone or something in a hostile and prejudiced manner. For example, "*Vaarallinen ilmastohörhelö, haittavihreä ja fanaatikko*." (A dangerous climate lunatic, a harmful Green and a fanatic.) is a stereotyping political tweet. Similarly, "*Toi Saramo on perus paska* [sic.] *vasemmistolainen*." (That Saramo is a basic crap leftist.) is also classified as a stereotyping political tweet.

As for other categories, "*Ei mennyt kahta viikkoa ennenkuin* [sic.] *akkalauma oli jo toistensa tukassa*" (It did not take two weeks for the bitch pack to start pulling each other's hair) is a gendered as well as a stereotyping tweet. Similarly, "*Sanna Marin* [sic.] *kommunistihallitus on poliittisen korruption ja kaksinaismoralosmin* [sic.] *kärkihanke. Keppihevostallin tytöt pyörittävät ministeri rulettia* [sic.] *ilman mitään substanssi osaamista* [sic.] *tai kokemusta ministerin tehtävistä.*" (Sanna Marin's communist cabinet is the spearhead of political corruption and double standards. Girls from the hobbyhorse stable run the minister roulette without any substantial knowledge or experience of minister tasks.) is both a gendered and a political stereotyping tweet. Note that there is a large number of typos in the tweets.

Regarding tweets that are sexualized, the Cambridge Dictionary (2023) defines the verb *to sexualize* as "to see someone or something in sexual terms, or to make someone or something sexually exciting." We expand this definition by including tweets that propose a sexual act. Tweets such as "*Olisikohan jotain yhteyttä omaan perverssioos?? i* [sic.]" (Does this have some connection with your own perversion?) and "*Portot kohtaavat Portossa*" (Whores meet in Porto) are both sexualized.

Many stereotyping tweets concerned immigrants, instead of ministers. Hence, we created an additional category for immigration-related stereotyping tweets even if we could have included them in the category of "Other stereotyping." For example, "*Otatko osaa maahanmuuttajien tappamille ja raiskaamille naisille? En vain ole huomannut.*" (Do you express your condolences for the women raped and killed by immigrants. I have not noticed.) is a stereotyping tweet targeted toward immigrants.

Empirical Strategy

The regression function (Eq. 1) includes variables for the minister's gender and political party. Political parties are included in the regressions as dummy variables, and the comparison group is the Centre Party. Hence, the results are interpreted relative to the ministers of the Centre Party. Similarly, the gender variable is a dummy variable taking the value of 1 when the minister is a woman. A positive and significant value for this variable indicates that women are more frequently targeted

by hate speech than men. The regression also includes a variable for the minister's age, which is similar to the studies by Southern and Harmer (2021) and Herrick and Thomas (2022). The age variable is a continuous variable measuring a minister's age in years. It mainly serves as a control variable, but it may give interpretable results. The results of Herrick and Thomas (2022) and Collignon and Rüdig (2020) showed that age decreases the likelihood of abuse.

$$\begin{aligned}\Pr(\text{hateful})_i = \alpha &+ \beta_1 \text{female}_i + \beta_2 \text{age}_i \\ &+ \beta_{3-6} D_{\text{party}} + \beta_7 \log(\text{followers})_i \\ &+ \beta_8 \text{female} \times \log(\text{followers})_i \\ &+ \beta_{9-14} D_{\text{weekday}} + \epsilon_i\end{aligned} \tag{1}$$

Further, the regressions contain different popularity measures. First, similar to Rheault et al. (2019), we use the Twitter follower count as a measure of a politician's visibility. The data for this variable were retrieved from Twitter. This variable interacted with the dummy variable indicating the female ministers.

Furthermore, Knuutila et al. (2019) argued that hate speech targets visible politicians, such as party leaders. Likewise, Herrick and Thomas (2022) showed that party leadership affects the likelihood of being targeted by different forms of abuse. Accordingly, we replace the visibility variable with two dummy variables (Eq. 2). The first variable indicates the five party leaders in the sample. This variable gets the value of 1 if the minister is one of the five party leaders, i.e., Sanna Marin, Maria Ohisalo, Li Andersson, Annika Saarikko, or Anna-Maja Henriksson. For the rest of the ministers, this variable gets a value of 0. Second, there is a dummy variable indicating the prime minister, i.e., Sanna Marin. Since women in visible positions may suffer more from hate speech, we expect that Prime Minister Sanna Marin faces more hate speech than other ministers, including the four other party leaders. Likewise, party leaders are expected to suffer more from hate speech than other ministers because they are more visible and have more political power.

$$\begin{aligned}\Pr(\text{hateful})_i = \alpha &+ \beta_1 \text{female}_i + \beta_2 \text{age}_i + \beta_{3-6} D_{\text{party}} \\ &+ \beta_7 \text{party leader}_i + \beta_8 \text{prime minister}_i \\ &+ \beta_{9-14} D_{\text{weekday}} + \epsilon_i\end{aligned} \tag{2}$$

The regression functions include control variables for the weekdays. Hence, there is a dummy variable for the days from Tuesday to Sunday. The comparison group is Monday. These variables are included because it is possible that hate speech is not distributed equally between the days of the week. In addition, the ministers may be active on Twitter on different days. Nonetheless, the results for these variables indicate whether hate speech targeting the ministers is more frequent during certain days of the week.

Furthermore, the role of masculine and feminine minister portfolios is examined by using dummy variables indicating the minister portfolios (Eq. 3). Hence, there are dummy variables indicating neutral and masculine minister portfolios. Moreover, these dummy variables have interacted with the dummy variable indicating the female ministers. Thus, the comparison group is male ministers that have a feminine

Table 1 Masculine, neutral, and feminine minister portfolios in Marin's cabinet

Minister	Gender	Portfolio
Masculine		
Tytti Tuppurainen (SDP)	F	Minister for European Affairs and Ownership Steering
Tuula Haatainen (SDP)	F	Minister of Employment
Sirpa Paatero (SDP)	F	Minister of Local Government
Annika Saarikko (Centre)*	F	Minister of Science and Culture/Minister of Finance
Maria Ohisalo (Greens)*	F	Minister of the Interior
Pekka Haavisto (Greens)	M	Minister for Foreign Affairs
Matti Vanhanen (Centre)	M	Minister of Finance
Timo Harakka (SDP)	M	Minister of Transport and Communications
Antti Kaikkonen (Centre)	M	Minister of Defence
Mika Lintilä (Centre)	M	Minister of Economic Affairs
Jari Leppä (Centre)	M	Minister of Agriculture and Forestry
Ville Skinnari (SDP)	M	Minister for Development Cooperation and Foreign Trade
Neutral		
Anna-Maja Henriksson (SPP)*	F	Minister of Justice
Sanna Marin (SDP)*	F	Prime Minister
Krista Mikkonen (Greens)	F	Minister of the Environment and Climate Change
Feminine		
Krista Kiuru (SDP)	F	Minister of Family Affairs and Social Services
Aino-Kaisa Pekonen (Left)	F	Minister of Social Affairs and Health
Li Andersson (Left)*	F	Minister of Education
Hanna Sarkkinen (Left)	F	Minister of Social Affairs and Health
Thomas Blomqvist (SPP)	M	Minister for Nordic Cooperation and Equality
Antti Kurvinen (Centre)	M	Minister of Culture and Sports
Jussi Saramo (Left)	M	Minister of Education

The minister portfolios are divided according to Krook and O'Brien (2012)

*Party leader

portfolio. However, as Table 1 shows, there are no male ministers that have a neutral portfolio. As a result, there is no interaction variable between the dummies indicating the neutral portfolios and the female ministers.

$$\begin{aligned}\Pr(\text{hateful})_i = \alpha &+ \beta_1 \text{female}_i + \beta_2 \text{age}_i + \beta_{3-6} D_{\text{party}} \\ &+ \beta_7 \log(\text{followers})_i + \beta_8 \text{neutral}_i \\ &+ \beta_9 \text{masculine}_i + \beta_{10} \text{female} \times \text{masculine}_i \\ &+ \beta_{11-16} D_{\text{weekday}} + \epsilon_i\end{aligned} \tag{3}$$

Table 2 shows the frequency of hate speech received by the minister. The figures show that there are large differences between the ministers in both the relative frequency and the absolute number of hateful tweets. This result is similar to that of Esposito and Breeze (2022). Tytti Tuppurainen, the Minister for European Affairs and Ownership Steering, faces the most hateful content both relatively and absolutely. She

Table 2 The relative frequency of hate speech

Name	Gender	Age	Followers	Minister's portfolio	Frequency	Hateful tweets	*n*
Tytti Tuppurainen (SDP)	F	45	15,700	European Affairs and Ownership Steering	0.122	97	797
Thomas Blomqvist (SPP)	M	56	3039	Nordic Cooperation and Equality	0.1	1	10
Pekka Haavisto (Greens)	M	63	168,000	Foreign Affairs	0.092	21	228
Matti Vanhanen (Centre)	M	66	17,100	Finance	0.077	1	13
Krista Kiuru (SDP)	F	47	23,200	Family Affairs and Social Services	0.074	25	340
Tuula Haatainen (SDP)	F	61	9607	Employment	0.07	7	100
Sirpa Paatero (SDP)	F	57	11,800	Local Government	0.067	13	195
Timo Harakka (SDP)	M	59	24,900	Transport and Communications	0.052	39	743
Anna-Maja Henriksson (SPP)*	F	57	21,700	Justice	0.049	12	246
Antti Kurvinen (Centre)	M	35	17,600	Culture and Sports	0.046	27	588
Sanna Marin (SDP)*	F	36	240,000	Prime Minister	0.045	54	1195
Jussi Saramo (Left)	M	42	10,400	Education	0.035	23	648
Aino-Kaisa Pekonen (Left)	F	42	21,200	Social Affairs and Health	0.034	7	203
Annika Saarikko (Centre)*	F	38	26,300	Science and Culture/Finance	0.033	24	720
Antti Kaikkonen (Centre)	M	47	30,700	Defence	0.032	21	657
Maria Ohisalo (Greens)*	F	36	81,700	Interior	0.03	33	1099
Li Andersson (Left)*	F	34	13,500	Education	0.028	14	500
Mika Lintilä (Centre)	M	55	16,000	Economic Affairs	0.028	8	287
Jari Leppä (Centre)	M	62	8875	Agriculture and Forestry	0.021	8	387
Krista Mikkonen (Greens)	F	49	17,600	Environment and Climate Change	0.018	17	951
Ville Skinnari (SDP)	M	47	8627	Development Cooperation and Foreign Trade	0.011	1	90
Hanna Sarkkinen (Left)	F	33	8550	Social Affairs and Health	0	0	49
Mean		44.7	36,186		0.045	20.6	456.6
Standard deviation		9.1	57,560		0.208	21.3	348.1
Total						453	10,046

The frequency is the share of hateful tweets of all the tweets received by the minister

SDP Social Democratic Party, *SPP* Swedish People's Party, *Greens* Greens Party of Finland, *Centre* Centre Party of Finland, *Left* Left Alliance, *Followers* number of Twitter followers in August 2021, *n* total number of tweets received by the minister

*Party leader

is followed by the Minister for Foreign Affairs, Pekka Haavisto. Hanna Sarkkinen joined the cabinet at the end of the sample period. Hence, her sample size is small, and it does not contain any hateful content. The figures also show that the Minister of Nordic Cooperation and Equality, Thomas Blomqvist, has only ten observations in the sample. As for Prime Minister Sanna Marin, her relative frequency of received hate speech equals the sample mean.

Table 2 also shows the number of followers of the ministers. The figures suggest that there are large differences between the ministers. The prime minister was the most followed Finnish minister on Twitter. Furthermore, the mean value for the number of followers of the five party leaders is 76,640. As for the other ministers, the mean number of followers is 24,288. Hence, the party leaders had, on average, about three times as many followers as the other ministers.

Regarding the classification into masculine and feminine minister portfolios, we follow the example of Krook and O'Brien (2012). Previously, Goddard (2019) showed that women are less likely to be appointed to masculine and neutral policy areas using a large sample of cabinet appointments in 29 European countries from 1985 to 2014. Likewise, Curtin et al. (2023) showed that women are more likely to be assigned to a feminine portfolio using a sample containing Australia, New Zealand, and Canada from 1985 to 2015. On the other hand, Höhmann (2023) used data on German minister appointments from 2006 to 2021 to show that the femininity of the ministry does not affect the appointments of female ministers. Contrary to expectations, parties in the German states are more likely to appoint a female minister if the policy area is highly salient for the governing party[8].

The classification is shown in Table 1. The prime minister is categorized as a neutral portfolio. However, it can be argued that the prime minister is a masculine portfolio because it has historically been a male position and a position of power. Krook and O'Brien (2012) did not include a prime minister in their classification. Thus, we ran robustness checks by classifying the prime minister as a masculine portfolio, which did not change our results. These results are not reported, but they are naturally available upon request.

Table 1 shows that the masculine minister portfolios comprise most of the cabinet ministers because 12 ministers hold a masculine portfolio. In addition, the distribution of portfolios is only slightly skewed by gender. First, there are five female ministers among the 12 masculine portfolios. Moreover, three of the seven feminine portfolios are held by men. As for the neutral portfolios, all three are held by women. Taken together, eight of the 15, i.e., the majority of neutral and masculine portfolios, are held by women. Hence, in contrast to Goddard (2019), women hold most of the masculine and neutral portfolios. However, similar to the findings by Curtin et al. (2023), women are slightly overrepresented in feminine positions. It is noteworthy that the first female minister of defence in Finland was Elisabeth Rehn from 1990 to 1995. She was the minister of defence in two different cabinets, and she was also the first European minister of defence. According to Barnes and O'Brien (2018), all other defence ministers before her were self-appointed. Moreover, women were

[8] Salience was measured using quantitative content analyses of parties' election manifestos. The variable captures the extent to which governing parties emphasize specific policy areas in their manifestos.

Table 3 Descriptive statistics for the frequency of hate speech by gender

	n	Frequency	Standard error	Standard deviation	95% confidence interval	
Male ministers	3651	0.041	0.003	0.199	0.035	0.048
Female ministers	6395	0.047	0.003	0.212	0.042	0.053
Total	10,046	0.045	0.002	0.208	0.041	0.049

The frequency is the share of hateful tweets out of all the tweets received by the minister

virtually absent from these posts before the end of the Cold War. In Marin's cabinet, the minister of defence is a man.

Table 3 shows the descriptive statistics for the frequency of hate speech by gender. The figures show that there is a small difference between the genders in the frequency. Female ministers are slightly more frequently targeted by hate speech. For male ministers, every 24th tweet is hateful. As for female ministers, every 21st tweet is, on average, hateful. This difference is not statistically significant. The *p*-value for the *t*-test is 0.1436. Furthermore, the figures show that the sample is larger for female ministers

Results

The results of the regressions are shown in Table 4. First, the results suggest that there is no systematic difference between female and male ministers in terms of the relative frequency of hate speech. The result is significantly positive in two regressions: those including the interaction variable between the female dummy and the visibility measure. Apart from these, the results for the dummy variables indicating women are insignificant. As for the ministers' age, the results of the two specifications suggest that a minister is targeted less by hate speech if he or she is older. Excluding these, the results for the age variable are insignificant.

Furthermore, the results consistently suggest that female ministers face fewer hateful tweets when they are more visible. First, this is indicated by the combined result of the log of the follower count and the interaction variable with the female dummy variable. Second, the coefficients indicating the five party leaders and the prime minister are both statistically significant and negative. Since all the five party leaders in the cabinet are women, this means that female ministers receive fewer hateful tweets if they are also party leaders. Moreover, since Prime Minister Sanna Marin is one of the five party leaders in the sample, she is targeted by hate speech even less than the four other party leaders[9]. Taken together, this suggests that the more political power a woman has, the less she is targeted by hate speech. This result is similar for all three visibility measures. Hence, we conclude that this result

[9] This result can be interpreted without including an interaction variable between the dummies indicating female ministers, party leaders, and the prime minister because all of them are women and the prime minister is also a party leader. Thus, the specification includes three dummy variables indicating the female ministers, the party leaders, and the prime minister.

Table 4 The effect of the study variables on the relative frequency of hate speech

Particulars	(1)	(2)	(3)
Female	0.020	9.387***	0.099
	(0.150)	(1.611)	(0.152)
log(followers)	−0.128	0.591***	
	(0.066)	(0.133)	
Female × log(followers)		−0.957***	
		(0.164)	
Party leader			−0.362*
			(0.183)
Prime minister			−0.549*
			(0.232)
Age	−0.004	−0.033**	−0.019*
	(0.009)	(0.011)	(0.009)
SPP	0.471	0.961*	0.854*
	(0.358)	(0.390)	(0.382)
SDP	0.856***	1.093***	0.927***
	(0.167)	(0.186)	(0.177)
Left Alliance	−0.094	−0.107	−0.111
	(0.200)	(0.199)	(0.193)
Greens	0.023	0.026	−0.060
	(0.199)	(0.214)	(0.190)
Tuesday	0.200	0.237	0.197
	(0.214)	(0.214)	(0.214)
Wednesday	0.160	0.177	0.193
	(0.202)	(0.202)	(0.202)
Thursday	0.157	0.122	0.117
	(0.206)	(0.206)	(0.206)
Friday	0.390*	0.377	0.374
	(0.196)	(0.196)	(0.196)
Saturday	0.610**	0.577**	0.587**
	(0.219)	(0.220)	(0.220)
Sunday	0.312	0.279	0.287
	(0.229)	(0.230)	(0.230)
Constant	−2.187*	−7.997***	−2.723***
	(0.999)	(1.298)	(0.472)
Observations	10,046	10,046	10,046

The dependent variable is a dummy variable that takes the value of 1 if the tweet is hateful. Otherwise, the value is 0. The coefficients are regression coefficients from logistic regressions. Standard errors are in parentheses

SDP Social Democratic Party, *SPP* Swedish People's Party, *Greens* Greens Party of Finland, *Centre* Centre Party of Finland, *Left* Left Alliance, *followers* number of Twitter followers on 21 August 2021

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

is robust. This result is strikingly different from the findings of Rheault et al. (2019), Herrick and Thomas (2022), and Håkansson (2021).

The ministers of the Swedish People's Party and Social Democratic Party receive more hateful tweets than other ministers. However, the result for the Swedish People's Party is significant only when the visibility measures have interacted with the female dummy variable. In any case, these results do not suggest that there is a systematic difference between the left and the right in the frequency of hate speech because the results for the ministers of the Left Alliance do not significantly differ from right-wing parties. Finally, there is a positive shock in the relative frequency of hate speech on Saturdays. This result is typically significant on Fridays as well.

Figure 1 shows the marginal effect of the female dummy variable on the impact of visibility on the hate speech frequency for the range of values for the log of the Twitter follower count. The figure is interpreted such that when the probability of zero is included inside the confidence interval, the result is statistically insignificant; that is, the female dummy variable has no marginal effect on the role of visibility. The figure shows that the result is significant for almost all the values of the log of followers. Hence, women are exposed to hate speech more than men when they are less visible. As opposed to this, female ministers are targeted by hate speech less than their male counterparts when they are highly visible. This result contrasts with that of Rheault et al. (2019).

Table 5 shows the results for the regressions that include dummy variables indicating the neutral and masculine minister portfolios. The first regression does not

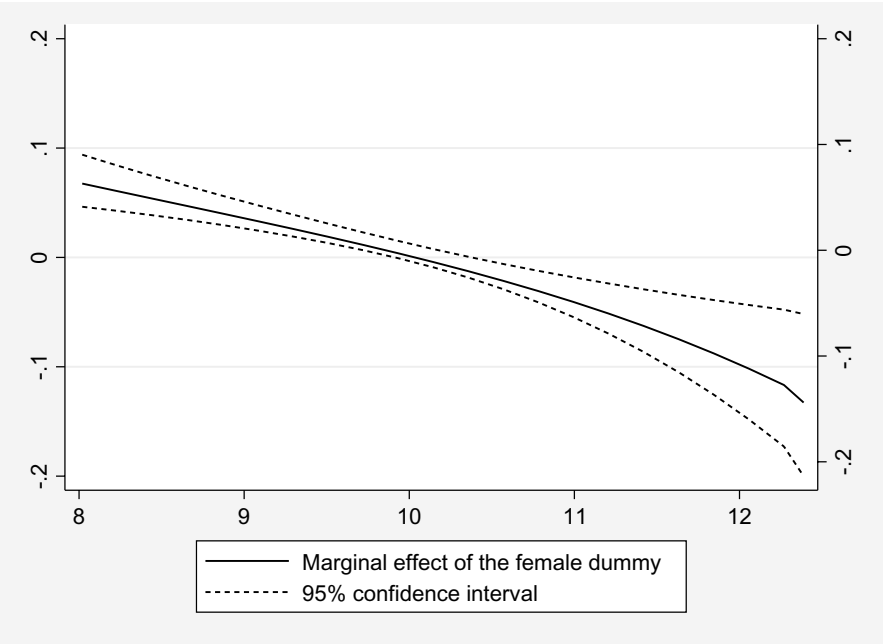

Fig. 1 Marginal effect of the female dummy variable on the role of visibility in hate speech

Table 5 Explaining the relative frequency of hate speech through the masculine/feminine minister portfolios

	(1)	(2)
Female	0.167	−0.410
	(0.153)	(0.215)
Neutral	−0.862***	−0.776**
	(0.229)	(0.239)
Masculine	−0.054	−0.940**
	(0.164)	(0.290)
Female × masculine		1.183***
		(0.315)
Age	−0.0003	0.026*
	(0.009)	(0.012)
log(followers)	0.071	0.234*
	(0.082)	(0.095)
SPP	1.115**	0.739
	(0.388)	(0.403)
SDP	0.885***	0.711***
	(0.165)	(0.178)
Left Alliance	−0.055	−0.072
	(0.219)	(0.217)
Greens	0.040	−0.208
	(0.202)	(0.217)
Tuesday	0.156	0.142
	(0.214)	(0.215)
Wednesday	0.130	0.145
	(0.202)	(0.203)
Thursday	0.077	0.067
	(0.207)	(0.207)
Friday	0.328	0.340
	(0.196)	(0.197)
Saturday	0.532*	0.524*
	(0.221)	(0.221)
Sunday	0.282	0.241
	(0.230)	(0.230)
Constant	−4.292***	−6.559***
	(1.101)	(1.263)
Observations	10,046	10,046

The dependent variable is a dummy variable that takes the value of 1 if the tweet is hateful. Otherwise, the value is 0. The coefficients are regression coefficients from logistic regressions. Standard errors are in parentheses

Neutral a neutral minister portfolio, *Masculine* a masculine minister position, *SDP* Social Democratic Party, *SPP* Swedish People's Party, *Greens* Greens Party of Finland, *Centre* Centre Party of Finland, *Left* Left Alliance, *followers* number of Twitter followers in August 2021

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

include the interaction variable. The results show that the neutral portfolios are targeted less by hate speech than the feminine or masculine portfolios. In other words, the masculine and feminine portfolios are targeted similarly to each other. Hence, there is no logical order for the likelihood of being targeted by hate speech in the sense that the likelihood does not gradually increase or decrease by the masculinity or femininity of the portfolio.

Interacting the dummies indicating the masculine ministries with the female dummy variable shows that there is no significant difference between the men and women holding a feminine minister portfolio. Since there are no men among the neutral portfolios, the neutral dummy variable indicates female ministers holding a neutral portfolio. Thus, there is no interaction variable between the gender dummy and the dummy indicating feminine ministries. The significant and negative coefficient suggests that these female ministers are targeted by hate speech less than the male and female ministers in the feminine ministries. This result is likely influenced by the fact that Prime Minister Sanna Marin has one of the neutral portfolios. Previous results (in Table 4) show that the prime minister is targeted by hate speech less than many other ministers.

The dummy variable indicating the masculine minister portfolios turns statistically significant when it is interacted with the dummy variable indicating female ministers. This means that the male ministers having a masculine portfolio are targeted less by hate speech than the male ministers holding feminine positions. Furthermore, since there is no statistically significant difference between the men and women in feminine positions, this means that the male ministers in the masculine ministries are less exposed to hate speech than the female ministers in the feminine ministries. Moreover, the dummy variable indicating the female ministers in the masculine ministries is statistically significant and positive. This suggests that female ministers are targeted by hate speech more than other ministers if they have a masculine portfolio. Taken together, these findings suggest that traditional gender roles are prevalent in Finland because ministers are more exposed to hate speech in "wrong" positions. We suggest that more studies are needed to explore gender-based hate speech in Finnish politics.

The results of the classification of 453 hateful tweets into stereotyping and sexualized tweets are shown in Table 6. First, about 18% (83 tweets) of the hateful tweets

Table 6 Stereotyping and sexualized hateful tweets by the ministers' gender

	Men	Women	Total	Frequency: men	Frequency: women	Total
Stereotyping tweets	26	57	83	0.0071	0.0089	0.0083
Stereotyping tweets: gender	4	13	17	0.0011	0.0020	0.0017
Stereotyping tweets: political	12	29	41	0.0033	0.0045	0.0041
Stereotyping tweets: immigration	9	16	25	0.0025	0.0025	0.0025
Stereotyping tweets: other	2	0	2			
Sexualized tweets	10	18	28	0.0028	0.0027	0.0028

The frequency denotes the share of stereotyping/sexualized hateful tweets of all the tweets received

were stereotyping tweets. Moreover, almost half (41 tweets) of the stereotyping tweets were political. In addition, 30% (25 tweets) of stereotyping tweets were targeted toward immigrants, not the ministers. Together, this means that a relatively small fraction of hateful tweets were stereotyping and gendered. The estimate, that is, 0.8% of tweets, is similar to that of Southern and Harmer (2021).

Even if the female ministers received most of the stereotyping tweets, the difference in the frequency between men and women is modest because the sample contains more observations of the female ministers. Furthermore, the differences in the frequencies of gendered and political stereotyping tweets are larger, but the frequencies are low. Most of the gendered stereotyping tweets targeted female ministers, but the total number of these tweets was low, with only 13 such tweets. Last, the 28 sexualized hateful tweets in the sample are divided between genders similar to the full tweet sample. Thus, the frequency is almost identical for both male and female ministers.

Since the number of observations is low, we do not want to make any far-reaching conclusions about the distribution of stereotyping tweets between male and female ministers[10]. Nonetheless, there are no substantial differences between male and female ministers in terms of the frequency of stereotyping or sexualized hateful tweets. In addition, all the frequencies are very low. These results are in strong contrast with those of Van Sant et al. (2021). Their results suggest that female politicians receive a large amount of sexualized and gendered stereotyping tweets. Moreover, our results are different from those of Bjarnegård (2023), Bjarnegård et al. (2022), and Erikson et al. (2021) who argue that hate speech targeting female politicians is often sexualized.

Conclusion

This study used a large, manually classified sample of tweets for examining hate speech targeting the ministers of the government of Finland. The cabinet in question was led by Prime Minister Sanna Marin. The results suggest that hate speech targeting the Finnish Ministers is common because, on average, every 20th tweet sent to the ministers of Marin's cabinet is abusive. However, there are large differences between the ministers because some ministers are frequently targeted by hateful messages. As opposed to this, some ministers suffer substantially less from hateful content on Twitter. This result is similar to that of Esposito and Breeze (2022).

The regression results did not suggest that female ministers are subjected to hateful tweets more than male ministers. This result is in line with the studies by Erikson et al. (2021) and Esposito and Breeze (2022). Nonetheless, it is likely that the minister's position affects the distribution of hate speech. For example, the minister of European affairs, the minister of foreign affairs, the minister of employment, and the minister of family affairs and social services were all frequently targeted by hate speech in a situation that was characterized by the COVID-19 lockdown,

[10] Statistical tests showed that all the differences are statistically insignificant. These results are not reported. Naturally, the test statistics are available upon request.

high unemployment, and the emotive immigration-related debate prevalent in Finland. Such factors may have induced abusive behavior targeting certain ministers. Moreover, the sampling period of this study was about 5 months, and it includes events such as the collapse of Afghanistan. A different sample might yield different results. Thus, we believe that studying a different sample in a similar setting is a good subject for further research.

We used the number of Twitter followers as a variable to measure a minister's visibility. In contrast to Rheault et al. (2019), our results did not suggest that a female politician's visibility increases hate speech targeting her. Instead, it seems that less visible female ministers are targeted by hate speech more frequently than more visible female ministers. The opposite is true for male ministers: more visible ministers are more often the targets of hate speech than less visible ones. This indicates that less visible female ministers may be perceived as less competent than their male counterparts as suggested by Rudman and Phelan (2008). However, it is unclear what factors may account for visible male ministers being targeted more frequently by hate speech than visible female ministers.

Furthermore, the party leaders and the prime minister received fewer hateful tweets than other ministers. Since the five party leaders in the sample and the prime minister are all women, these results are in strong contrast with those of Rheault et al. (2019), Håkansson (2021), and Herrick and Thomas (2022), who argue that women in visible positions are more frequently targeted by hate speech. Our results suggest that Finnish female politicians suffer less from hate speech when they have more visible positions. The leader of the Social Democratic Party, Prime Minister Sanna Marin, is targeted by hate speech even less than the four other party leaders.

The classification of the minister portfolios into masculine, feminine, and neutral categories and the subsequent analysis suggest that Finnish ministers may face traditional gender role expectations. This is because women with masculine portfolios were more exposed to hate speech than their male equivalents. Moreover, men with masculine portfolios were targeted by hate speech less than men in the feminine ministries, even if there is no statistically significant difference between men and women in the feminine ministries. This suggests that there are gendered patterns in online hate speech targeting the Finnish ministers. However, these patterns do not relate directly to gender itself. Rather, online hate speech targets those ministers that are not in their traditional roles. Even though Finland ranks well in international gender equality comparisons (e.g., European Institute for Gender Equality, 2022), Finland's job market is strongly segregated by gender (for example, see Statistics of Finland, 2021b). Hence, these results may imply a larger problem concerning gender roles. We propose that more research is required on this subject. Provided that the masculinity or femininity of a minister's portfolio affects the likelihood of being targeted by hate speech, one way to reduce hate speech, in the long run, is to appoint ministers without prejudices by breaking traditional gender norms.

We did not account for the possibility that hate speech targeting female ministers is harsher than hate speech targeting male ministers. Hence, even if the mean frequency of hate speech is identical for both men and women, it may be that female ministers are targeted by more (or less) abusive messages. However, we created a separate category for sexualized and stereotyping forms of hate speech. On average, three tweets out of every 1000 sample tweets were sexualized and abusive. The frequency of these messages was identical for the male and female ministers. The female ministers did encounter gendered stereotyping hateful tweets more often than their male colleagues, but the number of these tweets was low. This result is different from that of Saluja and Thilaka (2021), who argue that hate speech targeting female politicians is stereotyping and gendered. In this sample, stereotyping tweets were often targeted toward immigrants. The content was typically racist.

Furthermore, even if we were unable to find clear gendered patterns in hate speech targeting Finnish ministers, it does not necessarily suggest that hate speech is not gendered. Bardall et al. (2020) divided gendered political violence into three distinct elements: gendered motives, forms, and impacts. Despite the lack of gendered forms in this tweet sample, it may be that the motives of perpetrators are gendered. Similarly, the impacts of online hate speech may be gendered. For example, hate speech targeting female politicians may deter the participation of women in politics. Håkansson (2023) argued that psychological and physical violence leads women to be more likely than men to consider leaving politics. In addition, women are more likely than men to be silenced by violence.

Regarding political alignment, ministers from the Social Democratic Party and the Swedish People's Party are more often the targets of hate speech than other ministers. The cabinet composition may again affect these results. However, it may also be that a Swedish-speaking background induces hate speech. The two Swedish-speaking ministers were the only ethnic minority in Marin's cabinet of ministers. This is a clear weakness in this sample because it does not allow for the examination of the intersectionality of hate speech. Differently from Herrick and Thomas (2022) and Collignon and Rüdig (2020), we could not find a clear connection between age and the likelihood of being targeted by hate speech. Finally, the relative frequency of hate speech is higher on Fridays and Saturdays. The reason for this cannot be interpreted from these results, but alcohol may be a partial cause for this result.

It is important to discuss how well these results can be generalized. It may be that Finnish women do not face the same level of resistance as women in some other countries. Finland was the first country to have universal suffrage, and women's participation in politics[11] and the workforce is not a recent phenomenon. The President of Finland was a woman from 2000 to 2012, and Sanna Marin was the third female prime minister. Furthermore, the first Finnish female minister was in office from 1926 to 1927. Hence, many of our results may not be universally applicable. These results may simply derive from the fact that women's position in Finland's politics is stable and accepted. As a result, female ministers are not targeted more by hate

[11] Krook and O'Brien (2012) calculated a gender power score for 117 cabinets. This score measures a cabinet's gender balance by weighting minister portfolios by their masculinity/femininity and prestige. According to their calculations based on 2009 data, Finland's cabinet was the most balanced cabinet.

speech than their male colleagues. In any case, these results are in line with those of Southern and Harmer (2021), Esposito and Breeze (2022), Erikson et al. (2021), and Rheault et al. (2019). Building on these studies, we identify a nuanced relationship between gender and hate speech, demonstrating that the minister's portfolio significantly influences the likelihood of being targeted by hate speech.

Fellow researchers are strongly advised not to use machine learning algorithms for hate speech detection. According to what we learned while reading the tweets, users include intentional typos in their messages to prevent Twitter's hate speech filters. Moreover, the use of dialects, colorful informal language, typos, meme photos, and rich vocabulary make automated detection virtually impossible. In addition, many hateful tweets do not include any uncivil or otherwise hostile words (as noted by, e.g., Burnap and Williams 2015). Conversely, tweets may include incivility, such as swearing, without being hateful. In addition, 70% of the tweets identified as hateful did not contain any of the abusive keywords used by Knuutila et al. (2019). Hence, using a list of keywords excludes a large share of hate speech. Furthermore, the target of hate speech was someone else than the receiver of the message in 10% of hateful tweets in this sample. Excluding these tweets had no impact on our results.

Finally, there were three threats of violence in the sample of 10,046 tweets. They were sent to three different male ministers. It remains an unanswered question whether this skewness is caused by randomness or reflects the overrepresentation of men as victims of violence in Finland. Future research with a similar research setting and a different sample can shed more light on this matter.

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Data Availability The dataset has been published in Harvard Dataverse, with a permanent identifier. Since the data is Twitter data, tweet texts and other copyrighted material have been removed. https://doi.org/10.7910/DVN/MEHNOJ.

Declarations

Competing Interests The author declares no competing interests.

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