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Does Gender Still Matter for Politics? The Case of the 2018 U.S. Elections on Twitter

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1 For more information about the project visit our webpage: http://digitalsocietyproject.org

1 Introduction

Communication is the engine of mass politics, and the Internet has revolutionized communication both by elites and masses. Politicians increasingly use social media to communicate with voters during electoral campaigns (Jungherr, 2016), while citizens leverage it to directly address politicians and organize offline activism – one ground-breaking example being the #MeToo movement (Manikonda et al., 2018).

The growth of social media usage by politicians and citizens has brought political debates online, allowing scholars to study these interactions in a new context. This provides an opportunity to test how established theories travel to social media. In this paper, we investigate two dimensions of gender in politics. First, we study how gender stereotypes relate to the most discussed topics by candidates and their communication style online. Second, we examine whether female candidates are punished (electorally or otherwise) for deviating from previously established norms.

We examine the 2018 American midterm elections, a context in which social media saw wide campaign use (LaMarre and Suzuki-Lambrecht, 2013; Lee and Lim, 2016). We analyze the Twitter activity of all candidates for congressional or gubernatorial office, as well as the messages directed to those politicians by other Twitter users. These elections are particularly important because of the central place that gender issues played, following the #MeToo movement, and the Kavanaugh confirmation a month before the election. These elections were also pivotal for women as candidates, with the highest number of women ever running (and winning) in a national American election.

In the first part of our paper, we build on the work by Evans and Clark (2016), who similarly analyzed the 2012 U.S. elections, and compare their findings with those of 2018. We show that in the 2018 election campaign on Twitter, female candidates focused more on covering "women's issues" such as health-care and social protection compared to men, while male candidates talked more often about traditional "male issues" such as the economy and foreign policy. Further, we show that the age of the candidates, the state of gender equality in electoral districts, and the presence of other women candidates interacts with the extent to which there is a gender gap in the topics covered both by male and female candidates. Second, just as in the 2012 elections (Evans and Clark, 2016), we find that female candidates are more aggressive on Twitter, and this effect is not driven by female candidates being newcomers. In the second part of the paper, we interrogate whether stereotypes affect women's electoral performance and the likelihood of being harassed online. We find partial support for the double-standard proposition. In particular, talking about male issues decreases the likelihood of women being elected but it does not increase the likelihood of being targeted by angry speech online. Importantly, tweeting angrily is also a significant predictor of being elected and getting a higher vote share. At the same time, women who use angry speech on Twitter, are more likely to also receive tweets with abusive language, in particular by other women.

While we acknowledge that Twitter users are not representative of the whole population (Jungherr, 2016), we argue that it is important to study their reactions precisely because those Twitter users are more vocal and interested in politics than the average voter. Future research could compare data from Twitter with other types of data, for example, coming from experiments or from representative public opinion surveys. In addition, Twitter's near universal usage by candidates dwarfs the individual usage of any other particular social media platform in American politics. And with nearly a quarter million tweets posted by candidates in the eight weeks before the election, represents a treasure trove of how candidates choose to present themselves to the public. Further, the ability of normal users to tweet directly at politicians means that we can directly measure how members of the public respond to candidates with a precision unavailable through other techniques.

The paper contributes to the literature on gender norms and the framing of women's issues by candidates. The paper also advances our knowledge on how gender norms affect the candidate's electoral performance as well as the public reaction by gender to norm violations by candidates. This contribution is especially important due to the unequal representation of women in politics (despite record numbers, only a quarter of candidates in the midterms were women). Previous research has shown that this under-representation is partly due to the double-standards women face with regard to fitness for office: women ought to be kind and warm but leaders ought to be efficient and aggressive (Alexander and Andersen, 1993; Eagly and Karau, 2002). Female candidates face a dilemma of whether to present themselves as being more 'masculine' and thus more fit for office (Lee, 2013; Lee and Lim, 2016) while risking being perceived as too cold and insufficiently nice (Rudman and Glick, 2001).

Substantive strategies present their own challenge. Talking about traditional women's topics could be advantageous (Herrnson, Lay and Stokes, 2003), as due to stereotypes female candidates could 'own' important issues such as sexual assault (especially in the wake of #MeToo and Kavanaugh), school shootings, and the environment. However, doing so could also play into the negative stereotype that women are unable to deal with larger societal issues but will only focus on women's group interest (Diekman, Eagly and Kulesa, 2002). Previous research has shown that media is instrumental in curbing stereotypes and presenting female candidates with nuance (Bligh et al., 2012). Extending that research, the ability to leverage social media could allow female candidates to break those stereotypes, presenting themselves as nuanced candidates who can both stand for women's issues but also be aggressive and leader-like.

This article proceeds as follows: first, we discuss the existing literature and develop a set of hypotheses. Next, we discuss our empirical approach, including the operationalization of key concepts. We then test our hypotheses, and conclude with a discussion of our findings.

2 Theory

2.1 Gendering issues

Previous work has convincingly shown that gender matters for politics: men and women tend to have diverging policy preferences (Phillips, 1995; Khan, 2017), behave differently in legislatures (Saint-Germain, 1989; Thomas, 1991), and present themselves distinctly in campaigns (Kahn, 1993), including online (Evans, Cordova and Sipole, 2014; Evans and Clark, 2016).

Women tend to develop policy preferences distinct from men on social, economic, and political issues due to specific experience as a group (Khan, 2017; Sapiro, 1981*b*; Phillips, 1995). Empirical research has demonstrated these differences persisting across party lines, particularly in attitudes towards gender equality (Barnes and Cassese, 2017). Furthermore, women are socialized to be more concerned than men with taking care of others (Hutchings et al., 2004), while being disproportionately tasked with household work and child-care (Box-Steffensmeier, De Boef and Lin, 2004). As a consequence, women are more likely to be in favor of policies reducing the burden of care-taking obligations in particular (Bhalotra and Clots-Figueras, 2014), and equality in general (Ranehill and Weber, 2017; Almås et al., 2010). Further, women favor wealth redistribution more than men, even controlling for political ideology (Alesina and Giuliano, 2011; Iversen and Rosenbluth, 2006; Finseraas, Jakobsson and Kotsadam, 2012; Ranehill and Weber, 2017; Almås et al., 2010). Thus, women are more likely to support social welfare programs (Kaufmann and Petrocik, 1999), including those focusing on poverty alleviation, health-care, and education programs (Page Benjamin and Shapiro, 1992; Duflo, 2012). As such, a norm has developed considering social, equality, and family issues as being "women's".

This gap in preferences projects onto expectations of candidates. Women are seen as being better able to handle social issues in politics such as family, health, the environment, while men are perceived to be better equipped for dealing with issues such as the economy, foreign policy, and crime Sapiro (1981*b*); Sanbonmatsu (2002). Playing to the stereotyped strengths of their gender expected by norms can help candidates to attract in-group voters, while bucking gender norms has particularly hurt female candidates empirically (Kahn and Fridkin, 1996).

These patterns are well-grounded in decades of observation. For instance, in the 1984 and 1986 U.S. Senate campaigns, male candidates disproportionately discussed the economy, while women focused on social issues such as education and health-care (Kahn, 1993). This distinction seems to have transitioned robustly into the online world. In the 2012 U.S. House elections, Evans and Clark (2016) finds that on average women still cover "women's issues" more than men, and avoid traditional masculine issues. Similarly, when comparing the websites and Twitter presence of Clinton and Trump in the 2016 campaign, Lee and Lim (2016) finds that Clinton focused more on feminine issues than Trump, mentioning feminine issues at twice the rate of masculine ones.[1]

The convergence of gender issues and social media in the 2018 midterms make them a vital case to explore. The #MeToo movement went viral in 2017 as thousands of individuals shared personal stories of sexual abuse on social media. As of October 2018 the hash-tag MeToo had been mentioned more than 19 million times on Twitter (Pew Research Center N.d.). In addition, the sexual assault accusations leveled at Supreme Court nominee Brett Kavanaugh sparked enormous public response. The subsequent public hearing was watched live by 20.4 million people (Golum, N.d.). Both events significantly stirred the public discourse and were a major point of attention during the political campaigns both for men and women. On the day of Kavanaugh's hearing, 1 in 22 tweets from America mentioned him by name, a rate comparable to mentions of the Super Bowl on Super Bowl Sunday (Wilson and Gelman, 2018).

[1] While consistent, this finding is not universal. For instance, Dolan (2005) finds that female candidates for Congress in 2000 and 2002 did not present distinct issues from men.

How then do we expect the discussion of male vs. female issues by candidates to play out in the 2018 midterms? First, even without additional context, there is little reason to think that the gender divide in topical discussion apparent for decades would suddenly change. Second, given the historic moment of Kavanaugh and the #MeToo movement, it makes even less sense for female candidates to proportionally move away from women's issues. Failing to focus on them could be seen as failing to stand with women, with dire electoral consequences. This reasoning informs us to formulate the following expectation:

Hypothesis 1. *Female and male candidates alike will post Twitter messages that tend to follow the traditional gender division of topics.*

Certain conditions shape this hypothesis. First, generational replacement plays a key role in the evolution of societal values (Inglehart et al., 2003; Lyons, Duxbury and Higgins, 2005). American youth tend to be more liberal and supportive of progressive policies (Thompson, N.d.). For instance, 70% of Generation Z believes that the government should provide universal health-care (Ferguson and Freymann, N.d.). Representative Alexandria Ocasio-Cortez is a prototypical example of this new wave of politicians, with views aligned closely to the median for Americans under 40 (Ferguson and Freymann, N.d.). Therefore, we expect younger women to be more progressive, and less bound by historic gender norms governing candidate speech. Especially after the surge of female candidates in the 2018 elections, we expect younger women candidates to cover more often traditionally masculine topics.

Second, the gender dynamics of districts matters. As women become more financially empowered, the gender gap in policy preferences empirically has been observed to narrow, with women's interest in economic policies growing to match that of men (Edlund and Pande, 2002; Box-Steffensmeier, De Boef and Lin, 2004; Gottlieb, Grossman and Robinson, 2016). Therefore, we expect that in electoral districts where the pay gap between men and women is smaller, the gap in the covered policy issues should also shrink, with female candidates talking more about male topics.

Third, Evans and Clark (2016) convincingly argues that female candidates' focus on women's issues is an electoral strategy to distinguish themselves from male candidates. That strategic incentive disappears when a race is between two female candidates. Evans and Clark (2016) shows empirical support for this as the frequency of women's issue tweets declines as more women entered the 2012 elections. We expect to replicate this finding in the 2018 elections.

Therefore, we formulate the following hypotheses:

Hypothesis 2. *Female candidates will speak more about traditional male topics and less about female topics: A) as the candidates get younger; B) if they are running in more gender equal districts; and C) when they are running against another female candidate.*

Although this paper focuses on female candidates, we would expect similar (albeit inverted) patterns with male candidates. Younger men would be expected to break with topical gender norms. Men from less gender equal districts would be more likely to focus on traditional male issues. Male candidates running against women would be strategically disincentivized from talking about women's issues as it would decrease their capacity to distinguish themselves from their female opponent.

2.2 Men are aggressive; women are kind

Gender stereotypes are pervasive when evaluating the personal characteristics of candidates. Typical masculine traits are perceived as being strong, assertive, efficient, goal-oriented, while being kind, warm, compassionate, and family-oriented are typical feminine traits Lee and Lim (2016); Huddy and Terkildsen (1993); Banwart (2010). Importantly, research has found that these stereotypes are present among voters as recently as the 2008 elections (Banwart, 2010). These stereotypes punish female candidates, as voters consider aggression more important than compassion to succeed in politics (Banwart, 2010; Lee and Lim, 2016; Dolan, 2005), informing their tendency to consider men categorically more emotionally suited for office Alexander and Andersen (1993).

Female candidates adopt several strategies for combating this situation, such as discussing political issues significantly more often than male candidates (Evans, Cordova and Sipole, 2014) or emphasizing masculine traits. Lee (2013) finds empirical evidence for the latter when analyzing the biographies of congresswomen on their personal websites. Hillary Clinton decidedly emphasized masculine traits such as being strong, forceful, fighting, determined, effective (rather than caring, warm, understanding) both on her website and on Twitter during the 2016 campaign Lee and Lim (2016).

Furthermore, Evans, Cordova and Sipole (2014) finds that in the 2012 elections, female candidates were *more* aggressive online than their male counterparts. This is a strategic response to the stereotype, but also a function of female candidates being more likely to be challengers, who are more likely to use aggression to get noticed regardless of gender. This is intensified on social media, on which resource-constrained dark horses can distinguish themselves from traditional candidates Christensen (2013).

As such, we postulate that:

Hypothesis 3. *Female candidates are more likely to tweet aggressively.*

2.3 Public Response

Next we turn to public response to the behavior of female candidates, both in terms of electoral success and speech directed at candidates.

Gender stereotypes significantly influence how voters perceive candidates. Typically, voters believe male candidates can handle masculine issues (foreign policy, crime, economic issues) better than women, who are better at handling social issues (health-care, education) (Alexander and Andersen, 1993; Sapiro, 1981*a*, 1983; Kahn, 1993). This is driven by the assumption that women are more compassionate and thus better at handling issues related to caring for others (Fridkin and Kenney, 2009), while men are stereotypically more aggressive (and thus better equipped to deal with military), and more efficient (more qualified for economic issues) (Huddy and Terkildsen, 1993; Lammers, Gordijn and Otten, 2009). Further, due to these stereotypes, female candidates for office are often perceived as defending only the issues of women and not society overall (Diekman, Eagly and Kulesa, 2002).

Importantly, these gender stereotypes have been linked to voting behavior. Sanbonmatsu (2002) finds that at an individual level, these gender stereotypes explain the preference to vote for a man or a woman. Individuals preferring a male candidate also believe in the statement that men are emotionally better suited for politics, and think that men are better at handling traditional masculine issues (Sanbonmatsu, 2002; Falk and Kenski, 2006). In addition, women are more likely to vote for women, and think women will better handle traditionally female issues, especially abortion (whether pro-choice or pro-life) (Sanbonmatsu, 2002).

Finally, the salience of the issues in a particular election also matters for candidates' success. For instance, if crime is a particularly important issue in one election, male candidates might be in a relatively advantageous position as they are seen as been better able to deal with that issue (Kahn and Fridkin, 1996). For instance, a prominent explanation for the 1992 wave of elected women is the surge in voter interest in traditionally female oriented domestic issues following the end of the Gulf War and collapse of the Soviet Bloc (Dolan, 1998, 2005).

In the 2018 midterms, the key issues were overwhelmingly traditionally female: sexual violence (pushed to the forefront by #MeToo and the Kavanaugh nomination), as well as gun control and school shootings, climate change, and the continuing battle over Obamacare. Thus, we expect that campaigning on women's issues would in fact be a strategic advantage for women when they decide to "own" these issues (Herrnson, Lay and Stokes, 2003).

These stereotypes not only inform the topics voters perceive as appropriate for each gender, but the behavior they expect as well. This is especially problematic when gendered behavioral preferences are at odds with perceived qualifications for office. 'Perceived incongruity' occurs in people's minds when mutually exclusive stereotypes clash, namely how women are (caring, soft, kind) and how leaders should behave (aggressive, efficient) (Eagly and Karau, 2002). This is exacerbated when prescriptive gender stereotypes dictate that women should not be forceful or aggressive, the very qualities valued most in leaders and least in women (Prentice and Carranza, 2002). This results in prejudice against female candidates because demonstrating effective leadership simultaneously implies being a 'bad' woman according to traditional gender norms (Lee, 2013; Lee and Lim, 2016).

Experimental work has demonstrated that task-oriented women are perceived more negatively than other leaders (Forsyth, Heiney and Wright, 1997), that women perceived to be competent are seen as lacking warmth (Fiske et al., 2002), and that women are perceived as insufficiently 'nice' when acting agentic (Rudman and Glick, 2001). Each of these criticisms were ascribed to Hillary Clinton when running for office (Bligh et al., 2012). Turning to campaign management, experiments also suggest that emotionally neutral advertisements presented by women are perceived to be most socially desirable, while emotionally charged appeals (in particular, negative campaigning) hurt female candidates more than men (Hitchon, Chang and Harris, 1997). Of note is that experiments have shown that Americans consider anger in particular as less appropriate for women to express than men (Brooks, 2011).

As such, our expectation is that women who do not behave in accordance to candidate gender norms, that is women who deviate from traditionally female topics and are more aggressive, will be punished for it as formalized with this hypothesis:

Hypothesis 4. *Female candidates who do not follow the gender stereotypes will be punished both: A) electorally, and B) through more aggressive tweets from users.*[2]

Finally, we consider which group, men or women, would be more likely to punish female candidates for non-conforming with gender stereotypes. The literature on group behavior suggests that individuals are more likely to be sanctioned for transgression by members from their own group, ignoring similar behavior from out-of-group members, due to the expectation that the transgressors would be punished by their own group (Fearon and Laitin, 1996; Habyarimana et al., 2007). Although this research has largely focused on ethnic groups, we argue that the logic holds for other social identity groups. Supporting its applicability to gender is research showing that women and girls are more interested in politics when female role models participate in politics (Campbell and Wolbrecht, 2006; Jones, 2014).

Hanna Pitkin (1967) calls this 'symbolic representation': the representation of women in politics diminishes the stereotype that politics is a man's game. Historically, when compared to men, women tend to be less interested in politics (Burns, Schlozman and Verba, 2001), participate less in political activities (Verba, Burns and Schlozman, 1997), and know less about political issues (Jones, 2014).

However this changes as more women enter politics. Women can better articulate their own substantive policy positions when they are represented by a female senator (Jones, 2014), report being more interested in participating in politics (Campbell and Wolbrecht, 2006), and put more weight on policy congruence with female candidates (Jones, 2014: p.192). Finally, Cassese and Holman (2017) show that due to gender stereotypes, female candidates are particularly hurt by negative campaigning when attacks are aimed at traditionally strong female traits rather than male ones – a finding which goes in line with our expectation that in-group characteristics would matter for female candidates.

Building on this social group literature, Brooks (2011) hypothesize that women are more likely to punish other women when they conform with negative stereotypes that women are more emotional.

[2]We think it is important to emphasize the latter due to the rise of hate speech online in particular against women and minority groups (Article19, 2018).

They find partial support for their hypothesis: female candidates for office are electorally punished for crying, though they do not find that women punish female candidates disproportionately for anger. Despite this particular null finding, we believe that the body of theory still points to a disproportionate female response to female norm violation and as such we formulate the following expectation:

Hypothesis 5. *Female users will be more likely to punish female candidates for aggression.*

3 Data & Operationalization

To test our hypotheses, we collected three distinct sets of tweets in order to capture different aspects of Twitter activity leading up to the 2018 midterms. First, we collected all tweets posted by candidates for office, which provides the basis for a number of measures of candidate behavior. Second, we collected all tweets with text that matched a set of political keywords, giving us measures of how the public at large spoke about a variety of political issues. Third, we collected all tweets that had geocodes from within the United States, providing a baseline for what the public's speech looks like on Twitter across all subject areas, in addition to giving measures of the level of Twitter activity in each state and congressional district.

3.1 The Candidates

For the 2018 midterms, Twitter created a special subset of their verified account system such that candidates for office could register their Twitter accounts. Between this system and hand-coding of any missing accounts via Ballotpedia data and judicious Google use, we constructed a comprehensive listing of all Twitter accounts associated with major party candidates for the Senate, House, and Governors races in the November 2018 midterm elections. Most candidates had multiple Twitter accounts, which we labeled variously as personal, press, campaign, and officeholder, for a mean of 2.7 accounts per candidate. As a rule, we only collected data for Republican and Democratic candidates for each office, with the exception of the pair of third-party candidates who won office (Angus King and Bernie Sanders).

We found a total of 984 candidates for office in the midterms, only 26 of whom did not have active Twitter accounts. Every governor and senator candidate had active Twitter accounts, pointing to the higher professionalism and level of resources in those races. The 26 candidates without Twitter accounts were all losing House candidates, 24 of whom were Republican. None of these candidates had held elected office before, and each was running against a heavily favored incumbent. On average, these 26 candidates received only 26% of the vote in their respective House races. This basic pattern shows that Twitter is a nearly universal component of the campaign toolkit in American politics.

In order to collect Twitter data we built a custom system using the TweePy Python library. We downloaded the full timelines for all 2,646 Twitter accounts. We downloaded this data initially in mid-September and updated it once per week until the election. By downloading the data throughout the campaign we made it more likely that we would not miss tweets that were deleted after the fact, and in addition made sure that candidates who deleted their accounts after the election still had their activity captured. We built a Postgres database that contained tables for all candidate Twitter handles and tweets, with the latter including the full text of each tweet in addition to meta data such as the number of likes and retweets. For the purposes of this article, we limited our study to tweets by candidates for the eight weeks leading up to the election (from September 14th, 2018 until election day on November 6th, 2018). Candidates tweeted 237,387 times during this period.

3.2 The Public

We built a separate system in Java using Twitter's Streaming API in order to download keyword and geocoded matches from the population at large during the campaign. For the keyword streamer, we created a dictionary of 113 terms relevant to the issues and stories of this particular electoral cycle (listed in full in Table 7 in the appendix), in order to capture a picture of what American political speech in general looked like leading up to the election.[3] During the eight week timeframe of the study, this process collected the full text and metadata for approximately 190 million tweets, posted by 14 million different Twitter accounts.

For the geocoded tweets, we set up a separate streamer that collected *all* tweets within a latitude/longitude box encompassing North America. Note that only about 2% of tweets have attached geocodes, and those come in two varieties: precise latitude and longitude provided by the GPS of

[3] Thanks to Dr. Jeremy Gelman for his development of this list.

a smart phone, or approximate area of origin (generally at the city/town level) algorithmically determined by Twitter from other technical context. We developed custom GIS code to identify the state and congressional district of origin for each tweet. This amounted to an additional 74 million tweets.

For each user account, we extracted the 'name' field from the user metadata and took the first word as the likely first name. We estimated the likely gender of each user using a Python library (gender-guesser 0.4.0) that maps frequency of first name with gender based on several decades of US Census records. The result was an identifiable gender for 43% of users (of which 57% were male and 43% were female).[4] This allows us to disaggregate measures of public speech into gender.[5]

In addition, we searched all 190 million political tweets for instances where a user included one of the candidates' twitter handles in the text. Called 'mentions', these instances are visible to the mentioned account and as such are the primary way that people talk to each other via Twitter. That is, when someone mentions a candidate's twitter handle, they are explicitly making a statement to that individual. Of the political tweets, 9.3 million mentioned a candidate, for an average of 9,496 mentions per candidate.

Since we know the genders of the candidates and the public, we can disaggregate mentions into the four permutations of male at male, male at female, female at male, and female at female, capturing the multidimensional nature of gender dynamics in political speech.

3.3 Operationalizing Aggression

In order to measure aggression in tweets both by candidates and the public, we leveraged existing work by Colneric & Demsar that adapted Plutchik's classic model of different emotional states into an algorithm for identifying the dominant emotion present in a tweet. Plutchik's work classified emotion into eight broad categories of paired but contrasting emotion: joy & sadness, trust & disgust, fear & anger, and surprise & anticipation (Plutchik 1980). Colneric & Demsar's subsequent work trained a recurrent neural network (RNN) on the content patterns of 73 billion English language tweets, classifying their dominant emotion based on hashtags related to Plutchik's

[4]The well-documented hostility faced by women online makes the lower number of identifiable women expected.

[5]Where appropriate, we ran separate regressions in the subsequent data analysis sections using the 'unknown' gender tweets. The results tended to split the difference between the male and female results, suggesting that both the genders are present in roughly equal proportions in the unknown group, without anything systematic biasing our results.

labeling scheme. The result is a pre-trained algorithm that takes as an input the text of a tweet and provides as an output the statistical likelihood of the tweet's dominant emotion being each of Plutchik's eight categories.

We applied this algorithm to our collections of tweets, flagging tweets identified as 'angry'. We analyzed all candidate tweets, all mentions, a 1% random sample of all political tweets (1.9 million), and a 1% random sample of all geocoded tweets from the United States (740,000). The latter two were done on samples due to resource constraints, but this was deemed acceptable since the results are only used illustratively in aggregate, and the n is quite large anyway. Overall, only 1.1% of candidate tweets were angry, compared with 1.9% of geocoded tweets, 2.9% of political tweets, and 3.1% of tweets mentioning candidates. This makes intuitive sense: compared to the baseline (established by the geocoded tweets, which encompass any and all speech on American Twitter), Americans tweet angrier when they are talking about politics, and more so when they are directly tweeting at politicians. On the other hand, candidates tweet with *much* less anger than the public, reflecting their speech being official, professional, and subject to public scrutiny. In terms of operationalization, depending on the regression specification we use either the absolute number or percentage of angry tweets by/at a candidate.

3.4 Operationalizing Male and Female Issues

In order to operationalize male and female issues, we build heavily upon Evans and Clark (2016), who identified specific topic areas traditionally relegated to the male or female sphere of political discussion on Twitter during the 2012 House elections. Using their typology, we identified which of our political keywords would be male, female, or neither. Further, we used their existing list of keywords as additional signifiers of male vs. female topics, and added additional updated terms for the specific context of the 2018 elections (for instance, words associated with the Kavanugh hearing). We provide a full listing of these male and female dictionaries in the Appendix in Table 8. Note that only about half of the 190 million political tweets (and a similar proportion of the candidate tweets) in our dataset match either the male or female keyword list, so the two categories should not be considered as having a zero sum relationship. Figure 1 illustrates the proportion of all political tweets that matched either the male or female keyword lists over the course of the campaign. Note the enormous proportion of tweets matching the female list in the first half of the time period, which then drops to roughly equal proportions with the male list following Kavanaugh's confirmation.

Table 1 illustrates the differences in behavior and attributes of male and female candidates on Twitter. Female candidates tweet at a higher rate than male candidates, accounting for 35% of tweets among candidates although only comprising 29% of candidates. This is likely an artifact of the surge in young woman candidates in the 2018 midterm elections as well as their out-group status (Evans, Cordova and Sipole, 2014; Christensen, 2013). The bottom half of the table show the percentage of tweets posted by male and female candidates broken down by the operationalization discussed above. Women candidates tweet at a much higher rate of anger than male candidates (1.4% vs. 0.9%). In addition, male candidates tweet about male topics more than female candidates, and female candidates tweet about female issues at a much higher rate.

Next, tables 2(a) and 2(b) break down public behavior towards female candidates by the gender of the user (the rows) and disaggregated by the gender of the topic (the columns). The numbers represent the percentage difference between female and male candidates for each permutation, weighted by the total number of tweets by each gender of candidate. That is, if male and female candidates experienced proportionately identical behavior directed at them in their mentions, these numbers would all be zero percent. However, there is a staggering difference in most cases between women and men. First, in table 2(a) note that female candidates are tweeted at about female topics at a rate about 25% higher among both male and female members of the public. Compare that to table 2(b), in which *angry* mentions are directed at female candidates about female topics at approximately 40% a higher rate than at male candidates. Further, note that when discussing female topics, the rate of anger between male and female members of the public is essentially equal, but that changes drastically when talking about male topics. Men direct anger towards female candidates about male topics at a 9.6% higher rate than they do again male candidates, while the female public is *less* likely to do so. While these are primarily descriptive statistics (which we expand upon with a full suite of control variables in the next section), they are still highly compelling, painting a picture in which woman candidates are subjected to a great deal more anger than their male counterparts, and in which female members of the public play a significant role.

Figure 1: Time Series of Percentage of Political Tweets Matching Male or Female Topics

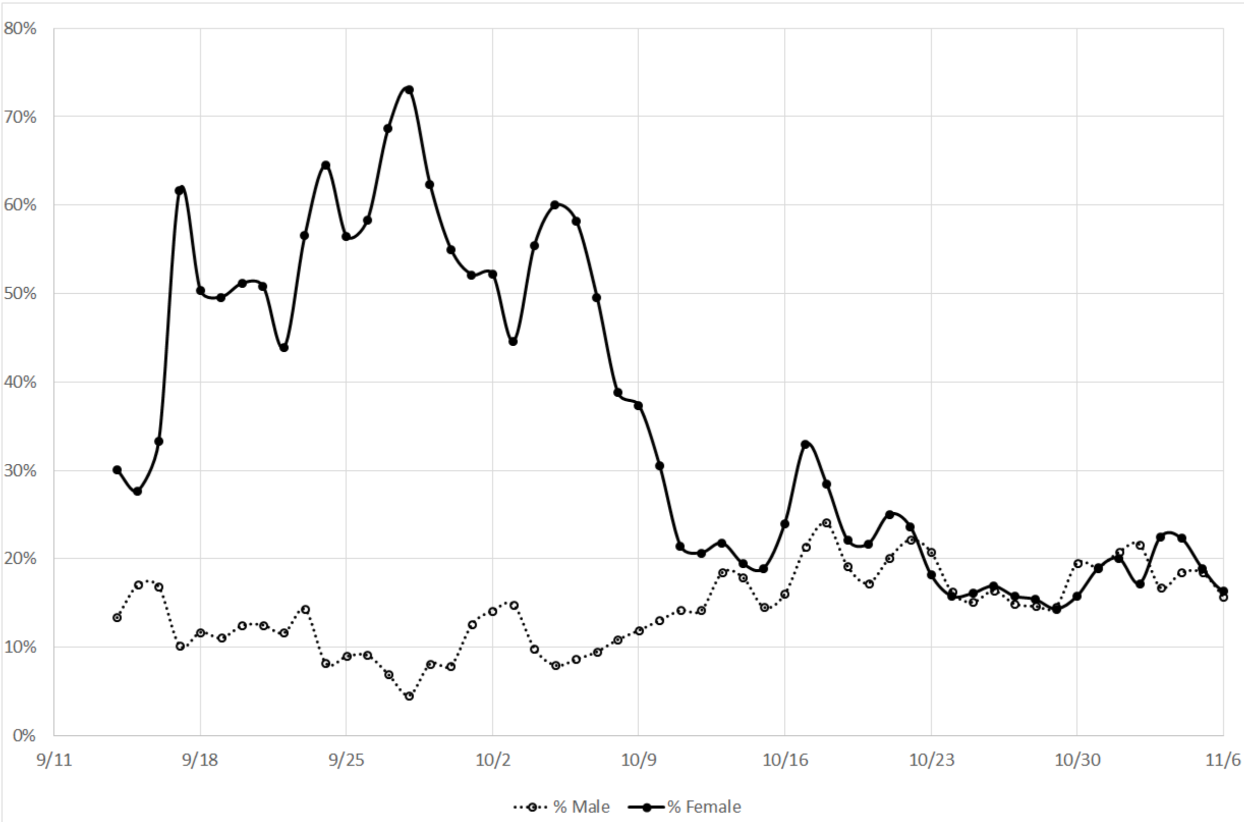


Table 1: Candidate Behavior/Attributes on Twitter

	Male Candidates	**Female Candidates**
# Candidates	683	275
% of Candidates	71.4%	28.6%
% of Tweets	64.8%	35.2%
% Angry Tweets	0.9%	1.4%
% Tweets about Male Topics	18.3%	15.2%
% Tweets about Female Topics	26.9%	35.6%

Table 2: Differences in Mentions Between Female and Male Candidates

(a) All Mentions

	Male Topics	**Female Topics**
By Men	-5.8%	+23.6%
By Women	-14.6%	+25.6%

(b) Angry Mentions

	Male Topics	**Female Topics**
By Men	+9.6%	+39.9%
By Women	-6.8%	+43.0%

3.5 Other Variables

We include several race-level variables in most subsequent regressions. First, *electoral ease* is how easy a generic candidate of the candidate's party should find the election based on the Cook's PVI rating for the district or state as appropriate. For instance, if the district was rated a Democrat+14 district, then this value is 14 for a Democrat running in the district and -14 for a Republican (the two third party candidates were treated as Democrats for the purposes of this measure since both lean heavily left). Second, to control for economic factors, we also use the logged median household income (labeled *income*) in each state or district (cite census bureau). Third, we include dummy variables for gubernatorial and senatorial races in order to capture systemic differences in those state level races. Fourth, we measure the general level of gender equality (labeled *gender gap*) in each state/district by calculating the wage gap between men and women, defined as: $1 - \frac{Income_M}{Income_F}$ (cite the ACS).

We capture electoral outcomes with two metrics: *vote share* is the percentage of the vote that the candidate won, while *won* is a variable indicating if the candidate won their election.

We have each candidate's age *age* from the Biographical Directory of the US Congress for any candidate who held office, and hand-coded for the remaining several hundred based on news articles, personal websites, and other databases such as VoteSmart. Twenty candidates (all of whom lost) had no information available that could be found.

In addition, we include variables indicating if the candidate was the *incumbent* (427 of 985), whether they ran *unopposed* by a major party candidate (38 of 985), whether they were a *quality candidate*[6] (581 of 985), and whether they faced a *quality opponent* (530 of 985).

Finally, we also include dichotomous variables indicating whether they were a *female candidate* (278 of 985), and whether they had a *female opponent* from the two major parties (253 of 985). The interaction of the latter two dichotomous variables produces a flag identifying woman against woman elections, of which there were 33.

4 Empirics

4.1 What candidates say

To test Hypothesis 1 whether candidates tweet more often about issues that are traditionally associated with their gender, we estimate negative binomial count regressions on the number of male and female topic tweets per candidate. The results are presented in Table 3 in models 1 and

[6] Defined as having ever held public office, data hand-coded by the authors based on biographies of all candidates (, N.d.)

2, respectively. As predicted, we find that being a female candidate has a positive and significant association with tweeting about female topics (model 1), and negative and significant association for male topics. That is, women talk more often about female topics, such as health-care, family issues, and education, and less about male topics, such as crime or the economy, even when controlling for common electoral covariates. Holding all other variables at their mean (or most common value for dichotomous variables), being a female candidate increases the expected proportion of female topical tweets by a candidate from 15% to 23%.

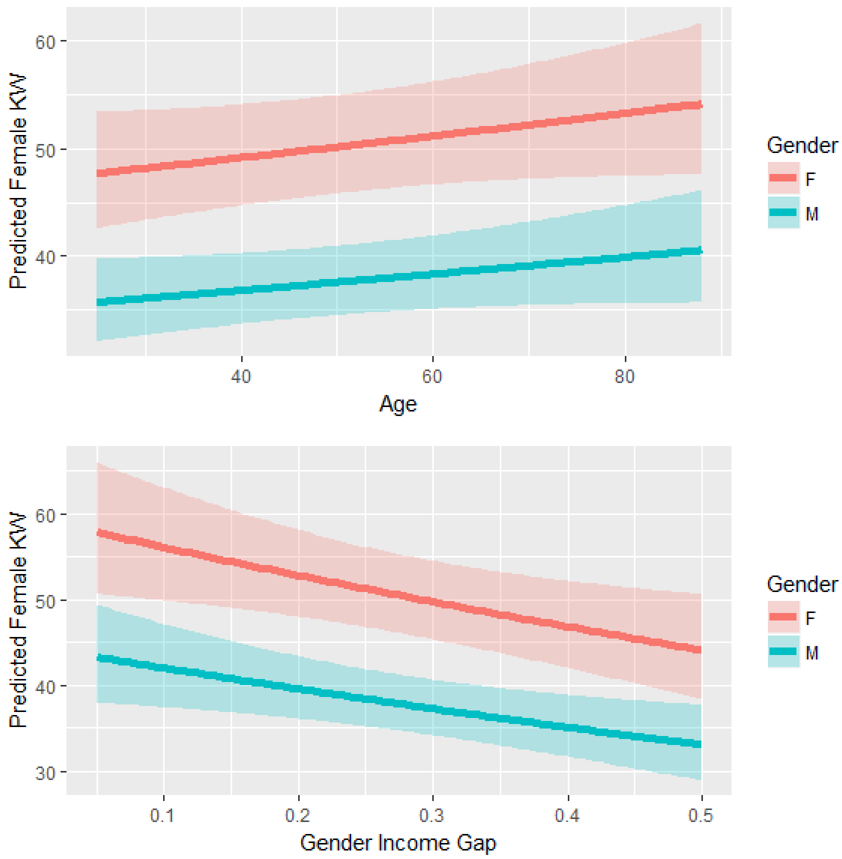
With Hypothesis 2 we seek to identify specific conditions for Hypothesis 1, interacting with age, gender equality of district, and opponent gender. Models 3 and 4 in Table 3 report regressions estimated on the subset of candidates that are women, while models 5 and 6 are estimated on the subset of candidates that are male. This allows us to examine independently the effects of these variables on each gender, which is appropriate as we hypothesized the effects within each gender as being independently generated processes.

The results for Hypothesis 2 are as follows:

- A) Generational differences between candidates. We find partial support for this hypothesis for women. As age goes up, discussion of female topics increases too. I.e. older women talk more about female topics as predicted (model 3). However, in model 4 we see that although the coefficient for age is in the expected direction (negative), it is not statistically significant. That is, we do not find robust evidence that younger women focus more often on male issues.
- B) Gender equality in terms of income. We find support for our hypothesis that in more equal electoral district, women are more likely to talk about "men's issues".
- C) Opponent gender. We find partial support for this hypothesis. Women are more likely to talk about male issues when running against another female candidate, which goes in line with our hypothesis (model 4). Although the coefficient for /emphfemale opponent is not statistically significant in the regression for female topics, it is in the right direction (negative), and the p-value is a tempting 0.20 (model 3).

In addition Figure 2 renders the predicted effects from Model 1 across the observed range of age and gender income gap, keeping all other covariates at their means (or most common dichotomous value). Both show the distinct trends observed above, and visual detail the stark difference between male and female candidates' topic selection on Twitter.

Figure 2: Estimated Effects of Candidate Gender on Female Topic Tweets



When looking at the inverted expectations for male candidates, we also find partial support for our predictions. The age of the candidate is not a significant predictor of choosing to talk about gendered topics. However, having a female opponent predicts talking more about male issues and less about female ones. Similarly, men in less gender equal constituencies choose to talk more about male issues.

When we turn to the results of other important covariates, we see that being an incumbent is significantly associated with talking about both the issues that we have identified as male and female for all candidates. The electoral ease to win elections is also a statistically significant predictor of more tweets on both topics, except for in model 4 and 5 (women tweeting on male topics and men about female ones). We see that both men and women with previous government experience (Quality candidate) talk more outside of the traditional topics for their gender (see models 4 and

Table 3: Negative Binomial Regressions of Male/Female Topical Tweets by Candidate

	All Candidates		*Female Candidates*		*Male Candidates*	
	Female Topics	Male Topics	Female Topics	Male Topics	Female Topics	Male Topics
	(1)	(2)	(3)	(4)	(5)	(6)
Female Candidate	0.289***	−0.166***				
	(0.030)	(0.040)				
Female Opponent	−0.097***	0.162***	−0.063	0.203***	−0.099**	0.138***
	(0.032)	(0.041)	(0.050)	(0.078)	(0.041)	(0.048)
Tweets per capita	0.029	−0.186**	0.060	−0.101	−0.020	−0.280**
	(0.060)	(0.080)	(0.071)	(0.116)	(0.092)	(0.111)
Electoral Ease	0.003**	0.005***	0.007***	0.001	0.001	0.007***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Incumbent	0.191***	0.331***	0.268***	0.326***	0.159**	0.328***
	(0.048)	(0.062)	(0.070)	(0.111)	(0.064)	(0.076)
Quality Candidate	0.041	0.011	−0.106	0.213*	0.104*	−0.054
	(0.048)	(0.062)	(0.071)	(0.111)	(0.063)	(0.075)
Quality Opponent	−0.022	−0.0002	−0.044	0.134	−0.015	−0.055
	(0.041)	(0.053)	(0.061)	(0.097)	(0.054)	(0.064)
Senate Race	−0.050	0.035	0.029	−0.069	−0.093	0.068
	(0.059)	(0.076)	(0.085)	(0.135)	(0.077)	(0.093)
Governor Race	0.040	0.047	0.171*	−0.088	−0.003	0.071
	(0.058)	(0.076)	(0.101)	(0.162)	(0.072)	(0.087)
Income	0.192***	0.062	0.201**	−0.084	0.154**	0.163*
	(0.059)	(0.077)	(0.086)	(0.136)	(0.079)	(0.093)
Age	0.002	0.001	0.004**	−0.001	0.001	0.001
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Gender Gap	−0.600***	1.023***	0.215	1.207**	−0.900***	0.823**
	(0.226)	(0.290)	(0.349)	(0.551)	(0.294)	(0.347)
Constant	−3.844***	−3.095***	−3.944***	−1.823	−3.315***	−4.090***
	(0.654)	(0.845)	(0.936)	(1.486)	(0.870)	(1.030)
Observations	941	941	272	272	669	669
Log Likelihood	-3,376	-3,237	-1,044	-963	-2,316	-2,267
Note:						*p<0.1; **p<0.05; ***p<0.01

5). At the same time, the quality of the opponent does not seem to matter for the choice of focus in online campaigns, neither does the position for which candidates are standing for election. The only exception is that women candidates for governors seem to talk more often about female issues. The income of the electoral district predicts more coverage of female issues both by men and women (models 3 and 5), as well as the coverage of male topics by men (model 6).

To sum up our findings, during the 2018 U.S. elections the candidate most likely to talk about women issues would be an older woman, incumbent, running against a male candidate, which represents a richer electoral district. Our findings predict that for this woman to switch talking about male issues more often, she would run in an election facing a female opponent, be a candidate with significant previous government experience, and come from electoral district with small gap in income between men and women. Male candidates are more likely to discuss female issues when they are running against another man, they are the incumbent or candidate with previous government experience, come from an electoral district with high income and relatively bigger pay gap between men and women when compared to other districts.

We next turn to the evidence for Hypothesis 3, which focused on thinking about whether female or male candidates would be more likely to tweet aggressive messages. To do that, we look at Table 4, model 1. This is OLS regression on the level of candidate anger in their tweets, and it is supported by the Female Candidate variable being positive and significant. It is important to note that the results are not driven simply by women being the newcomers in the race, as whether candidates are the incumbent, have previous government experience, and age does not seem to be associated with the likelihood to be angry on Twitter. Rather, the results suggest that female candidates coming from higher income electoral districts but with a more substantive gender pay gap, are those that are most likely to be angry.

Model 2 in the same table shows the results when estimated on the subset of women. Similar to the first model, we find that the gender pay gap is the only predictor of angrier tweets by female candidates.

4.2 Testing stereotypes through responses

We next move to test the expectations that not following traditional perceptions about what women should talk about and how, would hurt women both electorally, but it will also lead to more

Table 4: OLS Regressions of Candidate Anger

	Dependent variable: Candidate Anger	
	All Candidates	Female Candidates
	(1)	(2)
Female Candidate	0.002*	
	(0.001)	
Female Opponent	0.0003	0.002
	(0.001)	(0.002)
Tweets per capita	0.001	0.003
	(0.002)	(0.003)
Electoral Ease	0.00003	−0.00003
	(0.00004)	(0.0001)
Incumbent	0.001	0.0002
	(0.001)	(0.003)
Quality Candidate	0.0002	0.001
	(0.001)	(0.003)
Quality Opponent	0.0002	−0.001
	(0.001)	(0.003)
Senate Race	0.003	−0.002
	(0.002)	(0.004)
Governor Race	−0.004**	−0.007
	(0.002)	(0.005)
Income	0.006***	0.003
	(0.002)	(0.004)
Age	−0.00001	0.0001
	(0.00004)	(0.0001)
Gender Gap	−0.019***	−0.027*
	(0.007)	(0.015)
Constant	−0.039**	−0.003
	(0.020)	(0.043)
Observations	941	272
R^2	0.041	0.048
Adjusted R^2	0.029	0.008
Note:		*p<0.1; **p<0.05; ***p<0.01

harassment online.

Hypothesis 4 A (i.e. electoral punishment) is tested with Table 5. The first model is a logistic regression on the probability to win the electoral office, and the second model is OLS regression on the gained vote share. Again, we just look at female candidate subset since the hypothesis' scope is variation within female candidates.

We find that talking about male topics negatively impacts the candidate as hypothesized. However, opposite to the theory of gender stereotypes, being more angry helps female candidates get elected, as the positive and significant coefficients suggests for the regressions on the likelihood to win a race and get a higher vote share suggests (models 1 and 2). In terms of substantive impact, anger increased by one standard deviation increases expected vote shared by 1.8 percentage points. Male keywords increased by one standard deviation decreases expected vote share by 1.1 percentage points.

Finally, table 6 presents a negative binomial regressions on the number of angry tweets sent to female candidates by the public, broken down by all, male, and female users.

Hypothesis 4 B (i.e. women targeted by aggressive tweets) is tested in models 1 and 2, where it is partially supported. Candidate anger increases angry tweets at them, but not discussing male topics. In substantive terms, a one standard deviation increase in candidate anger leads to about 10 per cent increase in angry tweets. [7]

Hypothesis 5 is tested with Model 5 and 6 of Table 6 (whether it's women who punish women). Model 5 supports this with a positive and significant result, model 6 is in the predicted direction but not significant although it gets quite close with p value of 0.12. Again, the substantive effect here is about a 10% increase in angry tweets from the public per standard deviation shift in the candidate's anger. The same substantive effect in size is estimated for a shift in discussion of male topics. Further, note that none of the main independent variables of interest is statistically significant in models 3 and 4, i.e. female candidate behavior does not actually predict male anger towards them.

When looking at other important covariates, we see that having a female opponent reduces the likelihood to be a target of angry tweets. Being an incumbent is associated with increased risk for

[7] Note that the angry response our model is capturing could be due to angry support, and not punishment. We are not able to test this but we believe that it is less likely for twitter users to direct their angry messages at candidates they support.

Table 5: Logistic and OLS Regressions of Electoral Outcome

	Dependent variable:	
	Won Race	Vote Share
	Logit	*OLS*
	(1)	(2)
Candidate Anger	5.236**	0.182***
	(2.564)	(0.049)
Male Topics	−6.881**	−0.150**
	(3.009)	(0.074)
Female Opponent	0.268	−0.033***
	(0.490)	(0.012)
Tweets per capita	−0.947	−0.013
	(1.493)	(0.018)
Electoral Ease	0.165***	0.008***
	(0.030)	(0.0005)
Incumbent	2.342***	0.051***
	(0.697)	(0.017)
Quality Candidate	−0.640	0.012
	(0.661)	(0.017)
Quality Opponent	−0.773	−0.050***
	(0.559)	(0.015)
Senate Race	0.961	−0.017
	(0.882)	(0.021)
Governor Race	1.654*	−0.034
	(1.005)	(0.025)
Income	0.452	0.006
	(0.954)	(0.021)
Age	−0.019	0.00003
	(0.021)	(0.0005)
Gender Gap	2.506	−0.078
	(3.827)	(0.082)
Constant	−5.496	0.451**
	(10.440)	(0.226)
Observations	272	272
R^2		0.811
Adjusted R^2		0.801
Log Likelihood	-79	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 6: Negative Binomial Regressions of Public Anger (All, Male, and Female)

	Dependent variable:					
	Public Anger		Public Anger (Male)		Public Anger (Female)	
	(1)	(2)	(3)	(4)	(5)	(6)
Candidate Anger	4.184*		3.181		6.308*	
	(2.332)		(3.939)		(3.801)	
Male Topics		0.001		0.0003		0.002
		(0.001)		(0.001)		(0.001)
Female Opponent	−0.154**	−0.162**	−0.251**	−0.256**	−0.178	−0.196*
	(0.071)	(0.072)	(0.111)	(0.112)	(0.113)	(0.116)
Tweets per capita	−0.062	−0.038	−0.192	−0.187	−0.310	−0.276
	(0.115)	(0.116)	(0.195)	(0.197)	(0.205)	(0.210)
Electoral Ease	0.003	0.003	0.007	0.007	0.006	0.006
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Incumbent	0.178*	0.178*	0.176	0.184	0.202	0.203
	(0.100)	(0.101)	(0.155)	(0.156)	(0.154)	(0.158)
Quality Candidate	−0.031	−0.045	−0.177	−0.193	0.104	0.057
	(0.103)	(0.105)	(0.163)	(0.165)	(0.169)	(0.175)
Quality Opponent	0.096	0.076	0.005	−0.003	0.204	0.157
	(0.088)	(0.091)	(0.137)	(0.142)	(0.142)	(0.148)
Senate Race	0.324***	0.314***	0.336*	0.327*	0.190	0.183
	(0.114)	(0.115)	(0.175)	(0.175)	(0.170)	(0.173)
Governor Race	0.127	0.110	0.292	0.276	−0.326	−0.352
	(0.142)	(0.143)	(0.222)	(0.223)	(0.238)	(0.241)
Income	0.284**	0.286**	0.366*	0.370*	0.199	0.182
	(0.134)	(0.136)	(0.213)	(0.215)	(0.224)	(0.228)
Age	−0.006**	−0.005*	−0.008*	−0.008	−0.003	−0.001
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Gender Gap	−0.292	−0.370	0.796	0.692	−1.124	−1.206
	(0.551)	(0.551)	(0.883)	(0.879)	(0.939)	(0.945)
Constant	−6.558***	−6.505***	−8.765***	−8.733***	−7.456***	−7.176***
	(1.445)	(1.461)	(2.296)	(2.313)	(2.402)	(2.450)
Observations	272	272	272	272	272	272
Log Likelihood	-805	-806	-576	-577	-484	-484
Note:					*p<0.1; **p<0.05; ***p<0.01	

hate speech by the overall twitter public (model 1 and 2). Increased likelihood for receiving angry tweets is estimated also for older candidates, running for Senate and in richer constituencies, in particular, when it comes to hate speech by men (models 3 and 4).

5 Conclusion and next steps

Norms, in particular negative ones, have long stood in the way of electing more women to office. Media in particular has been shown to have strong role in shaping the perception of women politicians being cold or nice enough depending on the focus journalists takes (Bligh et al., 2012). This is where Internet presence becomes increasingly important, thanks to the ability of women and their teams to lead the conversation, and take control of a previously gendered narrative.

We find that during the 2018 U.S. election female candidates for office focused their discussion on issues we perceive as being traditionally female (such as health-care, sexual assault, LGBTQ rights, poverty, the environment, education and school shootings), and they were on average angrier than men on Twitter. More senior female candidates from richer districts talked most about traditonally female topics. Women facing another woman as opponent and those running in more gender equal districts talked more frequently about the traditional male issues such as the defense, budget, infrastructure, and agriculture.

We were also able to test whether stereotypes influenced voting patterns and reactions online. Contrary to the literature saying that women would be punished for showing emotions, female candidates who expressed more anger were more likely to be elected. Focusing on female issues also seems to be a winning electoral strategy, with increased focus on those issues increasing both vote share and winning probability of female candidates. In terms of hate speech online, we note that women are more likely to be the subject of angry tweets. These levels are enhanced as female candidates are angrier themselves, and are punished in particular by female users of social media.

The #MeToo era has sparked enormous public discussion of the politics of gender, and candidate interactions with the public via social media provide an invaluable insight into both the gendered tactics of candidates and the gendered responses of the public. While norms and stereotypes retain a powerful influence, they are being shifted, sometimes strategically, and sometimes through rage.

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6 Appendix

Table 7: List of political keywords captured from Twitter

#2A	#RedWave	Ivanka
#abolishICE	#religiousfreedom	Jong-Un
#BlueWave	#resist	Kaepernick
#BuildtheWall	#resistance	Kavanaugh
#climatechange	#ResistandWin	leftist
#coalminers	#RoevWade	MAGA
#confirmKavanaugh	#RussianCollusion	Manafort
#crookedhillary	#SCOTUS	Mattis
#Decision2018	#singlepayer	McConnell
#DeepState	#SpeakerRyan	medicaid
#DefendDACA	#SteeleDossier	medicare
#defundplannedparenthood	#StopKavanaugh	medicare-for-all
#draintheswamp	#TakeaKnee	Melania
#DreamAct	#TaxCuts	midterms
#EPA	#TaxCutsandJobsAct	minibus
#fakenews	#TCJA	MS-13
#FarmBill	#TradeWar	Mueller
#Fed	#TrumpEconomy	NAFTA
#FliptheHouse	#TurnOut	nuclear-free
#freetrade	#unionstrong	Obama
#fusiongps	#vote	obamacare
#gerrymandering	#VoteThemOut	Obama-era
#GOPTaxScam	#VotingRights	omnibus
#GovernmentShutdown	#WhiteHouse	Pelosi
#guncontrol	ACA	Pence
#HurricaneMaria	alt-right	Pompeo
#illegalimmigration	Antifa	Republican
#JobsReport	Biden	Roe
#keepfamiliestogether	Clinton	Schumer
#KidsInCages	collusion	Sessions
#liberalmedia	DACA	tariff
#LoveTrumpsHate	Democrat	Trump
#MAGA	denuclearization	WTO
#MuslimBan	DeVos	
#NeverHillary	DNC	
#ObamaEconomy	Donald	
#opiodcrisis	Dreamers	
#ParisAgreement	Gorsuch	
#prochoice	ICE	
#prolife	impeach	

Table 8: Division of male and female issues - Words and phrases.

Female topics	Male topics	Male topics
health care	defense	ms 13
aca/obama care/affordable care act	military	daca
medicare for all	veteran/veterans/va/vets	dream act
single payer	weapons	ice
social security	nuke/nuclear	daca
medicare/medicaid	biological	dreamers
equality	chemical	abolish ice
welfare	terrorism	kids in cages
food stamps	foreign policy	illegal immigration
snap	international relations	tcja
wic	foreign affairs	trade war
tanf	war	tariff
child/children	iraq	nafta
kid/kids	afghanistan	wto
women/female	syria	free trade
girl/girls	iran	build the wall
poverty	benghazi	gun control
family/families	homeland security	minibus
educate/education	11-Sep	2a
abortion	dream act	nato
pro-choice/pro choice	border	government shutdown
pro-life/prolife	border security	memorial
war on women	immigration	omnibus
birth control	amnesty	
plan b	farm	
rape	agriculture	
domestic violence	legalization	
gay marriage	pot	
doma	marijuana	
prop 8	liberty	
environment	guns	
binders full of women	business	
paris agreement	economy	
kavanaugh	tax/taxes	
metoo	budget	
planned parenthood	wage/wages	
care	government spending	
teacher	nsa	
community	spying	
school / school shooting	debt	
equal pay	inflation	
lgbtqia/lgbtq/lgbt	infrastructure	
marriage	roads	
social	north korea	
#defundplannedparenthood	honor	
roe v wade/roe vs wade	amendment	
climate change		

Table 9: Descriptive statistics

Variable	Female Democrats	Female Republicans
# Candidates	214	64
# Male Topic Tweets	76,98	130,11
# Female Topic Tweets	237,86	101,44
Candidate Anger Level	0,03	0,02
# of Tweets Total	581,71	449,06
Female Opponent	0,17	0,48
Tweets per capita	0,24	0,27
Electoral Ease	0,27	-2,83
Incumbent	0,34	0,33
Quality Candidate	0,49	0,55
Quality Opponent	0,64	0,66
Senate Race	0,07	0,13
Governor's Race	0,06	0,05
Income	60687,84	60615,06
Age	53,96	52,67
Gender Gap	0,27	0,26
# of Mentions Total	6622,53	3017,77
Won Race	0,51	0,28
Vote Share	0,53	0,42
# of Angry Mentions	243,52	85,23
# of Angry Mentions by Men	57,33	19,69
# of Angry Mentions by Women	44,93	15,47