# Women Use More Positive Language than Men: Candidates' Strategic Use of Emotive Language in Election Campaigns 

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#### Abstract

How do candidates strategically use emotive language during elections? Whereas government candidates and incumbents are incentivized to use positive language to incite support for the status quo, opposition candidates and challengers deploy negative sentiment to foster voter discontent. Women candidates, though, face a double bind, making it less likely they benefit from negative language and limiting the strategies at their disposal. Leveraging approximately 165,000 tweets from 2,662 British candidates, we show women are more positive and less negative than men, regardless of their government/incumbent status. Subsequent sentiment analysis of over a million replies indicates why this may be the case: women are penalized for negative emoting- garnering more negative replies and fewer likes than men. Together, these findings suggest women are not simply socialized to be more positive, but also, they are strategically motivated to behave in gendertypical ways to appeal to voters and avoid backlash on the campaign trail.


Key Words: women candidates; emoting; campaign; sentiment analysis

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Women confront a myriad of unique obstacles on the path to political office (Bauer 2020; Bernhard, Shames, and Teel 2021; Cassese and Holman 2018; Teele, Kalla, and Rosenbluth 2018). Faced with discrimination, women candidates are more likely to behave strategically on the campaign trail, innovating to gain the edge they need to compete with men candidates (Wagner, Gainous, and Holman 2017). For instance, women carefully craft the content of their campaign messages, often emphasizing issues that voters associate more favorably with women candidates, to improve their electoral fortunes (Herrnson, Lay, and Stokes 2003).

When it comes to campaign messages, how politicians use language-not merely the content of their language-matters (Boussalis et al. 2021; Dietrich, Hayes, and O’Brien 2019; Hargrave 2022; Hargrave and Blumenau 2022). Though experimental research has long shown that campaign messages can manipulate emotional responses and influence voting behavior (e.g., Marcus, Neuman, and MacKuen 2000; Utych 2018), observational research has only recently demonstrated that parties (Crabtree et al. 2020) and individual legislators (Osnabrügge, Hobolt, and Roden 2021) take advantage of this strategy—deploying emotive language to sway voters. Despite this growing attention to how and when parties and politicians use emotive language (Valentim and Widmann 2021; Widmann 2021), a burgeoning body of research on legislative speeches (Bäck and Debus 2019; Bäck, Debus, and Fernandes 2021a; Hargrave and Blumenau 2022; Hargrave and Langengen 2021; Slapin et al. 2018; Slapin and Kirkland 2020; Weeks 2009), and widespread public and scholarly interest in women's pathways to power (e.g., Shames, Bernhard, Holman, and Teele 2020), research has not considered how the individual-level characteristics of politicians-such as gender-influence their strategic use of emotive language.

We theorize that because positive emoting has the propensity to trigger emotional responses among voters-ultimately influencing their behavior at the polls-individual candidates also have an incentive to strategically use emotive language during campaigns. Building on the existing literature,
we argue that members of the government party and incumbent candidates have a stronger incentive to engage in positive emoting to incite support for the status quo. Members of the opposition and challengers, by contrast, are more motivated to use negativity to cultivate discontent with the current state of affairs.

Not all candidates, though, benefit equally from the use of emotive language. Women challengers and opposition members, in particular, may face a double bind during campaigns (Schneider and Bos 2014), making it less likely that they benefit from negative emoting as much as their men counterparts. Whereas men are stereotyped as being tough and aggressive, women are expected to be compassionate, gentle, and likable (Huddy and Terkildsen 1993; Bauer 2020; Cassese and Holman 2018). Although men can effectively use negative emoting, women candidates deploying the same strategy may be met with backlash. Consequently, women candidates affiliated with the opposition party and women challengers, fearing sanction for violating gender stereotypes (Krupnikov and Bauer 2014; Ono and Yamada 2020), may be less likely than men to engage in negative emoting-giving them one less weapon in their arsenal for effectively navigating the campaign trail.

To test our theoretical expectations, we developed a novel dataset that captures the emotive language from approximately 165,000 tweets posted by 2,662 candidates for the House of Commons in the runup to the 2017 and 2019 British elections. Given that the vast majority of candidates use Twitter during the campaign, our data features extensive variation on the government/opposition and incumbent/challenger status of women and men candidates competing in over 1,000 contests. We show that incumbents and members of the government party are more likely to use positive emoting. Challengers and members of the opposition, by contrast, are more likely to leverage negative sentiment. That said, these patterns are different for women than men. Women candidates engage in more positive, and less negative, emoting than men with the same
government/incumbency status. We contend that this pattern emerges because women are more likely than men to be met with negative reactions when they engage in negative emoting.

In addition to asking whether women emote differently than men, we probe the extent to which this is an effective strategy. We argue that if women present themselves as more positive than men to avoid alienating voters, we should observe evidence of backlash from citizens when women violate gendered expectations and engage in negative emoting. A sentiment analysis of more than one million responses to candidate tweets shows that women are, indeed, penalized more than men for negativity. Negative sentiment in women's campaign messages garners more negative replies and fewer likes than men's, despite similar levels of overall engagement. These findings suggests that women are not simply avoiding negativity because they are socialized to behave more positively than men, but rather that women strategically deploy emotive language to navigate the double bind and appeal to voters.

Combined, our findings shed light on the complex ways that political campaigns are gendered and deepen our understanding of how politicians use emotive language to advance their position. In doing so, our results provide an optimistic view of women candidates exercising agency. Specifically, we show that, rather than being passive recipients of commentary about their emotional states, women candidates actively and strategically manage their emotional appearance to incite positivity and minimize negative responses from voters. At the same time our results illustrate the ongoing challenges women face in politics. Going negative has long been seen as a useful campaign strategy—particularly for challengers and those in the opposition. That women must avoid negative sentiment to circumvent reprisal from voters means they have fewer strategies available to them during elections.

## Gender and Campaigns

Political campaigns are inherently gendered (Anzia and Bernhard 2022; Smith 2021; Cassese and Holman 2018; Krupnikov and Bauer 2014). Women are less likely to be recruited to run for office (Kenny 2013; Lawless and Fox 2005), display lower levels of ambition (Bos et al. 2022; Schneider et al. 2014), and ultimately are less likely to opt to throw their hat into the ring (Bernhard, Shames, and Teel 2021; Thomsen and King 2020). During campaigns, women are subject to gendered evaluations. In some circumstances, women (and men) can benefit from feminine leadership styles (Bernhard 2021). That said, voters tend to hold masculine expectations of candidates (Schneider and Bos 2021), resulting in higher and sometimes "shifting" standards for women (Bauer 2021). Thus, women must be better qualified than men for voters to view them as equal (Bauer 2020). Women may also be differentially affected by attack ads. Although women weather some types of attack ads better than men (Fridkin, Kenny, and Woodall 2009), they are particularly vulnerable to attacks that imply they violated gender stereotypic behavior (Cassese and Holman 2018) and ads that frame women as the instigator of negativity (Krupnikov and Bauer 2014).

Given the barriers faced by women candidates, it is important to understand how they navigate campaigns differently than men. Indeed, the strategy for getting ahead at the polls is not the same for everyone, and gender shapes elections in very nuanced ways. Evidence from US elections shows that women can gain an edge by running "as women" and emphasizing issues that voters associate with women (Herrnson, Lay, and Stokes 2003). Yet others contend that women candidates do well to adopt "masculine" campaign strategies (Windette 2013) and even face backlash when the content of campaign messages reinforce gender stereotypes (Bauer 2015). Importantly, gendered campaign messages are not limited to women. Images from Twitter during UK elections show men use masculinity in campaign messages (Smith 2021). Research on negative campaigning is also nuanced. Whereas some research on the US Senate elections shows women are less likely to go
negative (Kahn and Kenney 2000), others find women candidates for the US House invoke more disgust (Russell et al. 2022) and tweet more attack style messages (Evens and Clark 2015).

Beyond the messages they craft, how women candidates deliver their messages may be critical for navigating the gendered dynamics of campaigns. Indeed, scholars of gender and politics recognize the importance of women's communication styles for understanding how they succeed in politics more generally (Bäck, Debus, and Müller 2014; Costa 2021; Dietrich, Hayes, and O’Brien 2019; Hargrave and Langengen 2021; Weeks 2009). We know much less, however, about how women deliver messages during campaigns to traverse gender dynamics in elections. We add to this body of research by examining women's and men's use of emotive language during campaigns.

## Emoting on the Campaign Trail: A Political Strategy

How candidates communicate their campaign message matters. A long line of experimental research shows that the sentiment of campaign messages can be manipulated to induce emotional responses and influence voting behavior (Marcus, Neuman, and MacKuen 2000; Utych 2018). Campaigns can use images, music, or vocal tones in an effort to strike an emotional chord and capture voters' attention (Brader 2005; Lau and Rovner 2009). Despite these pervasive findings from experimental research, until recently scholars have not considered whether politicians and political parties actually use emotional sentiments to influence voters. New observational research evaluating party manifestos demonstrates that political parties take advantage of this strategy—using campaign sentiment to garner votes at the polls (Crabtree et al. 2020). And, recent work on individual legislators shows that politicians also strategically deploy emotive language to appeal directly to voters during parliamentary speech (Osnabrügge, Hobolt, and Roden 2021; Valentim and Widmann 2021; Widmann 2022). We contribute to this line of research by explaining why individual candidates leverage similar strategies during political campaigns.

To begin, the incumbent's performance in office typically serves as a focal point in campaigns (Ferejohn 1986). Whether voters choose to support the incumbent depends on their perception of government policy performance (Lewis-Beck and Stegmaier 2000). Voters, though, do not form their impressions in a vacuum. Elites can use their campaign messages to shape citizen's evaluations, craft their perceptions of objective facts, and alter the salience of policy performance in a given election (Chong and Druckman 2007; Utych 2018; Zaller 1992; Vavreck 2009; Williams, Seki, and Whitten 2016). Since emotive language has the propensity to trigger emotional responses among voters (Chong and Druckman 2007; Utych 2018; Zaller 1992)—ultimately influencing their decisions at the polls-individual candidates have an incentive to use emotive language strategically (Osnabrügge, Hobolt, and Roden 2021).

We argue that the extent to which candidates engage in positive or negative emoting is likely to vary depending on their incentives. We reason that both members of the government and incumbents are incentivized to use more positive sentiments than members of the opposition or challenger candidates, respectively. Since the government party has been controlling the national policy agenda and elections are typically viewed as a referendum on the government, members of the government can expect to benefit at the polls when voters view the status quo favorably. The same logic applies for incumbents, particularly in countries with personal vote seeking incentives such as the United Kingdom (Fleming 2021). Whereas the government controls the national policy agenda, individual members of parliament (MPs) propose private bills, promoting policies important to their constituents to establish an electoral connection in their district (Bowler 2010). Elections thus likewise serve as a referendum on the incumbent MP's track record (Pattie, Hartman, and Johnston 2017).

For this reason, government and incumbent MPs have an incentive to cast the current state of the world in a positive light. They can use positive emoting to incite support for the status quo
(Crabtree et al. 2020). Positive campaign sentiment can engender positive feelings among voters and garner more electoral support for the government and incumbent MPs. Consequently, compared to members of the opposition and challengers, they have a stronger incentive to use positive sentiment in their campaign messaging.

H1a: Members of the government will use higher levels of positive sentiment in their campaign messages than members of the opposition.
H1b: Incumbent MPs will use higher levels of positive sentiment in their campaign messages than challengers.

Whereas all candidates have some incentive to use negative emotions, members of the opposition party and challengers have a stronger incentive to deploy negativity than members of the government and incumbents. Since the government is responsible for crafting the national policy agenda, and incumbent MPs control policies targeting their district, candidates from the opposition party and challengers are incentivised to sow discontent with the status quo. Their only hope of being successful at the polls is to convince constituents that there is a need for leadership change. In crafting their message, opposition MPs/challengers want to wield negative sentiment to invoke adverse feelings towards their opponent and manufacture discontent with the state of the world (Utych 2018).

Beyond casting the status quo in a negative light, opposition MPs and challengers can use negative sentiment to induce voters to pay more attention to their own policy messages. This is because negative emotional appeals induce voters to be more attentive (Marcus, Neuman, and MacKuen 2000) and provoke a reevaluation of both candidates' qualifications and track records (Lau and Rovner 2009). Given that negativity may incite questioning in the minds of voters, almost all candidates are motivated to use negative sentiment at some point during the campaign. But, challengers and members of the opposition are likely to confront this incentive more often. Since government's/incumbent's policies serve as focal points of the election, the opposition faces the
challenge of drawing attention to their own policy positions. Negative messaging can craft an image of a competent leader who is holding the government/incumbent to account (Carraro and Castelli 2010)—encouraging voters to consider alternative policies in lieu of the status quo (Druckman, Kifer, and Parkin 2010). Consequently, we anticipate that members of the opposition party and challengers are more likely to engage in negative emoting.

H2a: Opposition MPs will use higher levels of negative sentiment in their campaign messages than members of the government.
H2b: Challengers will use bigher levels of negative sentiment in their campaign messages than incumbents.

## Women Candidates and the Strategic Use of Emotional Sentiment

The conventional wisdom that informs our understanding of campaign dynamics may be useful for anticipating how men candidates can leverage emotive language differently depending on their government and incumbency status. Yet women candidates confront different dynamics. Women face what is commonly known as a "double bind," where voters' expectations for how women should behave are incongruent with voter's expectations for political leaders (Eagly and Carli 2007; Schneider and Bos 2014). Whereas men are expected to be strong and aggressive, women are expected to be positive, warm, gentle, and likable (Schneider and Bos 2019). Gender role congruity theory suggests that because politics has long been dominated by men, political leaders are associated with masculine traits, giving men (who typically possess such traits) an advantage in the electoral arena over women (Eagly and Karau 2002).

Women politicians, however, cannot simply compensate for this incongruity by embodying masculine traits. This is because although voters tend to value masculinity in political leaders (Bauer 2020), they also want leaders to act in gender-congruent ways (Eagly and Carli 2007). When evaluating political leaders, people apply common gender stereotypes to their expectations about
men and women candidates. But when women candidates conform to expected gender stereotypes, they are likely to be rewarded. Violating gender stereotypes, by contrast, can elicit negative responses. Put differently: "what might be a positive quality for a man could be a negative quality for women" (Schneider and Bos 2014: 261). To this point, research on women candidates finds that, on average, women are more likely to be rewarded for positive emotional displays, and punished for negative ones (Boussalis, Coan, Holman, and Muiller 2021; Cassese and Holman 2018).

Combined this research suggests that women candidates may have an incentive to use more positive sentiment than men candidates. But, as we explained above, depending on their incumbency and/or government status, candidates sometimes have an incentive to invoke negative sentiment. If women want to be successful at the polls, they are thus left to navigate both incentives cultivated by their government/incumbency status and the incentives to exhibit gender-typical traits.

For women in the government party and women incumbents, their incentives largely align: As members of the government/incumbents, they are motivated to engage in positive emoting to signal support for the status quo. As women, they have an incentive to deploy positive sentiment to cultivate a warm, likable persona. Women may even be able to more effectively convey their campaign message when they engage in emoting. Research on women lawyers, for instance, finds that women are more likely to win legal battles when they use more affective language (Gleason 2020). Women legislators are more persuasive in getting men to vote in favor of legislation when they speak with more emotional intensity (Dietrich, Hayes, and O'Brien 2019). And, in campaign debates, voters respond more positively to women politicians for positive emotional displays (Boussalis, Coan, Holman, and Muiller 2021). Consequently, women incumbents have an incentiveabove and beyond the incentive fostered by their government and incumbency status-to adopt positive emotive language.

H3a: W omen government MPs will use bigher levels of positive sentiment in their campaign messages than men government MPs.
H3b: Women incumbent MPs will use higher levels of positive sentiment in their campaign messages than men incumbent MPs.

For women opposition candidates and challengers, the task may be more difficult. Recall members of the opposition party and challengers have an incentive to engage in negative emoting. This strategy may work well for men, who are expected to be strong, aggressive leaders, but it may not be as effective for women. Women must break with gender-typical behavior to engage in negative emoting. As a consequence, they may face backlash from voters (Bauer 2017). Consistent with this argument, experimental research on negative campaigning finds that women are punished more than men for going negative (Herrnson et al. 2003; Hitchon et al. 1997)—especially when women are viewed as the instigator (Krupnikov and Bauer 2014). Similarly, research evaluating citizens' responses to video footage of German Chancellor Angela Merkel's political debates demonstrates that, unlike her male counterpart, she was punished for showing negative emotions (Boussalis, Coan, Holman, and Muiller 2021). Given that women are likely to face punishment when they engage in negativity, we anticipate that despite the incentives fostered by their opposition/challenger status, women are motivated to curb their negative sentiments on the campaign trail.

H4a: Women in the opposition will use lower levels of negative sentiment in their campaign messages than men in the opposition
H4b: Women challengers will use lower levels of negative sentiment in their campaign messages than men challengers.

## Evaluating the Use of Emotive Language on the Campaign Trail

To evaluate our theoretical expectations, we developed a new dataset capturing the emotive language used in tweets by candidates from parties competing for a seat in the British House of Commons. The United Kingdom provides an ideal, most likely case setting to examine how candidates deploy emotive sentiment in their campaign rhetoric. First, in a Westminster style parliament like the UK, party cohesion is typically very high (Slapin et al. 2018). The party is responsible for setting the national policy agenda, engineering a strong national level campaign, and controlling the campaign message. Consequently, candidates' campaign rhetoric is tied to their status as a candidate for either the government or opposition. This context is useful for evaluating our theory because if party cohesion were especially low, and there were no national campaign strategy, government/opposition status would exert far less influence over candidates' campaign messaging.

At the same time, in the UK, local election strategies and individual candidates' campaign efforts matter (Pattie, Hartman, and Johnston 2017). British voters value a direct link with their MP (Fleming 2021). Owing to the personal-vote-seeking incentives generated in the single-member district constituencies, individual MPs work hard to develop a personal vote, promoting legislation that targets their constituents (Bowler 2010). As much as elections are a referendum on the government, they also serve as a check on the incumbent MP (Pattie, Hartman, and Johnston 2017). Individual candidates, thus have an incentive to develop their own campaign message above and beyond the national party's message.

Finally, that candidates compete in single-member districts, and not on a closed-list proportional representation ballot, means both women and men have incentives to cultivate their own campaign strategy. If candidates were competing on a closed-list, they would have little incentive to ever deviate from the party platform, making it very difficult to detect any differences between women's and men's campaign behavior. But, since all candidates face personal-vote-seeking
incentives, if women and men have different incentives to use emotive language, we should be most likely to observe these differences in settings like the elections for the House of Commons.

## Observing Candidate's Campaign Messages: Evidence from Twitter

To evaluate our theoretical expectations regarding the use of emotive language in candidates' campaign messaging, we turn to Twitter. Scholars are increasingly using Twitter data to understand politicians' political messages in office (Russell 2021; Smith 2021; Wagner, Gainous, and Holman 2017), and to evaluate their campaign behavior (Stier et al. 2018).

Twitter offers several advantages compared to other media for candidates. As Stier put it, Twitter "enable[s] candidates to directly reach out to voters, mobilize supporters, and influence the public agenda" (Stier et al. 2018, 50). At the same time, research finds that their online behavior on Twitter and other campaign platforms largely replicates their traditional campaign messages and styles (Gibson, Römmele, and Williamson 2014; Larsson 2015; Lilleker et al. 2011; Stromer-Galley 2000). Even though there is some selection bias in terms of the citizens who choose to use Twitter, an analysis of candidates' campaign messaging suggests that candidates tend to have a "mass audience" in mind when campaigning on social media (Stier et al. 2018, 51). Unlike other types of messaging, Twitter is available to all candidates and not constrained by campaign finances. Equally important, research from elections in the UK suggests that Twitter campaigns are effective for helping candidates to win votes (Bright et al. 2020). Given these advantages, Twitter has become a vital campaign tool in many elections across the globe—including the British Elections (Smith 2021; Bright et al. 2020).

The benefits Twitter offers candidates translate into at least five advantages from a research design perspective. First, that Twitter is used to target a "mass audience" (Stier et al. 2018) is useful because it means findings from Twitter are likely to be generalizable beyond the platform. Second,
unlike other campaign mediums, Twitter analyses can readily include all tweets from the period understudy. Since all of the data are displayed on a single platform, we do not have to design a sample of campaign messages to target. And there are far fewer concerns that some subsets of messages have been systematically excluded from our data collection as may be the case if we were trying to collect all flyers, mailers, or other material generated by candidates and disseminated via other mediums. This is particularly important if we assume that candidate gender might be related to missingness, as that would mean our analyses would likely be vulnerable to 'post-treatment' bias (Montgomery et al. 2018). Third, Twitter facilitates the analysis of a large number of candidates. Although it may not be reasonable to analyze the behavior of all candidates competing for national parliament in observational studies considering other types of campaign material, we can easily gather data on all candidates on the platform. This feasibility combined with the near-ubiquitous use of Twitter in the British Elections (Bright et. al. 2020) is necessary for ensuring we can draw relevant comparisons between women and men, incumbents and challengers, and government and opposition candidates. Fourth, free access to Twitter means that almost all candidates can use the platform, ensuring that campaign finances do not constrain candidates' decisions to emote negatively, positively, or use a mix of both types of sentiment. When using more costly forms of campaign material, candidates must make tough choices based on limited resources. On Twitter, campaign incentives like the ones posited above, and not finances, constrain candidates' behavior. For this reason, Twitter is a particularly attractive platform for analyzing campaign sentiment.

Finally, in the case of tweets, we can also observe and analyze direct reactions to campaign messages. This is difficult if not impossible to do with other campaign materials, such as flyers, outside of the lab.

## Data Collection

Our analysis focuses on the two most recent elections for the House of Commons. We select all candidates from the five parties with the largest vote shares in each of two elections. Candidates competed across six parties: Conservatives, Labour, Liberal Democrats, Scottish Nationalist Party, UK Independence Party, and Brexit Party. We collected this sample of tweets through the "follow" functionality of the Twitter Streaming API, which allows users to supply a list of Twitter accounts and receive a stream of tweets related to these accounts, including the tweets from these accounts, replies, likes, and retweets. In attempt to maximize the number of candidates included in our analysis, we use crowd-sourcing to expand on an existing list of candidate Twitter accounts from Democracy Club. ${ }^{1}$ Specifically, for candidates who did not have Twitter accounts on the Democracy Club list, we asked workers on Amazon Mechanical Turk to look for the candidates' accounts from the name and party affiliation. We identified accounts for $70 \%$ of all candidates from the included parties in 2017 and $87 \%$ in 2019. ${ }^{2}$ We collected tweets for each candidate from two weeks before the election up until a day before the election, for a total of 165,041 tweets posted by 2,662 candidates ( 75,897 tweets by 1,484 candidates in 2017 and 89,144 tweets by 1,829 in 2019). ${ }^{3}$ We also collected replies to the candidate tweets, which we use in a subsequent analysis.

## Measuring the Use of Emotive Language

One of the innovations of our research is that we employ observational data to evaluate emotive language used by candidates in the runup to election. We coded the sentiment of tweets using a

[^0]dictionary-based method to account for the proportion of positive and negative words in individual tweets. We use the Harvard-IV sentiment dictionary included in the SentimentAnalysis package in R to score all tweets in our sample. This dictionary contains 2,005 positive and 1,637 negative words, has been repeatedly validated, and is widely used in social science applications (e.g., Dietrich et al., 2019).

To test our expectations, we analyze the positive and negative scores separately. Each positive or negative score ranges from 0 to 1 with higher values indicating stronger positive or negative sentiment. For candidates, the average positive (negative) score is 0.18 (0.08) with a standard deviation of 0.14 (0.10). Average sentiment scores of candidate tweets across gender, party status, and incumbency status are available in Appendix Table A.5. ${ }^{4}$

## Independent V ariables of Interests

To test H1a and H2a, we created a binary variable coded 1 to indicate the candidate is a member of the government party and 0 to indicate they are a member of the opposition. To test H 1 b and H 2 b , we created a binary variable coded 1 to indicate the candidate is an incumbent MP, and 0 if they are a challenger. We anticipate that both government MPs and incumbents will be more likely to use positive sentiment than members of the opposition or challenger candidates and less likely to engage in negative emoting, respectively. To evaluate our second set of hypotheses, we also created a binary indicator for whether a candidate self-identified as a woman using the official data for election outcomes provided by the House of Commons Library. Women represent 35.4 percent of candidates using Twitter across the two elections. We then included two interaction terms, one between government MP and woman and a second between incumbent and woman to assess

[^1]whether women from the government party (H3a and H 4 a ) and women incumbents ( H 3 b and H 4 b ) emote differently than their men counterparts.

## Modeling Strategy

To test our expectations, we estimate the relationship between campaign sentiment, incumbency status and gender using ordinary least squares (OLS) regression models. The unit of observation is an individual Tweet. As we have both positive and negative measures of campaign sentiment, each ranging from 0 to 1 , for each tweet, we analyze separate regression models for positive and negative sentiment. The model includes fixed effects for election years and the 12 regions in the UK. To account for possible heteroscedasticity, we cluster standard errors by candidate (i.e., the level of the treatment variable $W$ oman ).

## Analyzing the Use of Emotive Language on Twitter During Campaigns

Figure 1 shows the regression coefficients for key variables (full models available in Appendix Table B.1). The left panel analyzes the use of positive sentiment; The panel on the right analyzes negative sentiment. Turning first to H 1 a and H 1 b , consistent with our expectation, the left panel in Figure 1 displays a positive and significant relationship between members of the governing party and their use of positive sentiment. We likewise observe a positive relationship between the incumbency status of candidates and positive sentiment, indicating that both members of the government party and incumbents engage in more positive emoting during campaigns than do opposition MPs or challengers.

In contrast, we anticipated that members of the opposition and challengers would use more negative sentiment (H2a and H2b). The right panel in Figure 1 shows the relationship between negative emoting and candidate status. The negative and significant coefficients for the variable

Government indicate that members of the government use less negative sentiment than members of the opposition. The negative coefficient for Incumbent likewise shows that incumbent candidates engage in less negative emoting than challengers. The results in the right panel of Figure 1, thus provide support for our expectations that opposition MPs and challengers are more likely to deploy negative sentiment in their campaign messages.

The results displayed in Figure 1 also evaluate how campaign sentiment differs for men and women candidates. We observe that, on average, women engage in more positive emoting and less negative emoting on Twitter than their men counterparts. Interestingly, candidate gender is overall an equally strong (or in some cases stronger) predictor of the use of emotive language than other key predictors. For positive emoting, gender is a stronger predictor than government party membership, suggesting that incentives to behave in gender-congruent ways outweigh incentives to use emotive language to generate support for the government's performance. Similarly, for negative emoting, gender is a stronger predictor than incumbency status.

With that being said, we are particularly interested in how women navigate campaigns differently than men with the same incumbency/government status. To assess $\mathrm{H} 3 \mathrm{a} / \mathrm{b}$ and $\mathrm{H} 4 \mathrm{a} / \mathrm{b}$, we turn to models that include an interaction term between Women and Government (triangles in Figure 1); and models that include an interaction between Women and Incumbent (squares in Figure 1). The interactions allow us to assess whether women emote differently depending on their government (triangles) and incumbency (squares) status. The coefficient plot shows that the relationship between women and government status is a significant correlate of both positive and negative emoting. And the relationship between women and incumbency status is a strong predictor of negative emoting.

$\boldsymbol{\phi}$ (1) $\boldsymbol{\phi}$ (2) $\boldsymbol{\phi}$ (3)

Note: Dependent variable for the left panel is the level of candidate tweet positivity, and the right panel is the level of negativity. Model 1(circles) does not include interaction, Model 2 (triangles) includes Government and Woman interaction, and Model 3 (squared) includes Incumbent and Woman interaction.
Figure 1: Regression Coefficients for the Candidate Tweet Sentiment Models

To illustrate these relationships and facilitate the interpretation of the interaction terms, Figure 2 plots the expected level of positivity (left panel) and negativity (right panel) across different situations. The top panel focuses on the government/opposition status of the candidates (based on Model 2 for both the positivity and negativity DVs) and the bottom panel displays candidates by their incumbency/challenger status (based on Models 3). The expected value for men is indicated by the dark circles and the one for women is displayed using light circles.


Note: The plot shows the predicted level of Positivity (left) and Negativity (right) in candidate tweets across candidate types (top) and status of the party (bottom). There are separate predictions for candidate gender - woman (gray) and man (black). The predictions are generated from models with interaction terms. The top row predictions are from Models 2 and 5, and the bottom row predictions are from Models 3 and 6 . The bars denote $95 \%$ confidence intervals.
Figure 2: Predicted Level of Negativity and Positivity in Candidate Tweets

The first thing to notice from these figures is that, on average, members of the government are more positive and less negative than members of the opposition. Incumbent members are likewise more positive and less negative than challengers. This is consistent with the results displayed in Model 1 that evaluate the direct effect of candidate status, and with prior work by Crabtree et al. (2020). The plots thus offer additional support for our first two sets of hypotheses. There is, however, important variation by candidate gender and status which we elaborate on below.

Turning to the differences between women and men, the effect of gender is always salient across all sub-groups. That is, women are always more positive and less negative than men with the same government/incumbency status. Importantly, however, when we look across the four panels, the expected level of positivity and negativity for women and men candidates varies across the different dyads or subgroups. Notably, we observe a consistent pattern for both women from the governing party and women incumbents wherein they use higher levels of positive sentiment than men. In fact, although the differences in men's and women's level of positivity is always significant, the largest difference observed is among government candidates, where women's level of positivity is about 0.020 higher than men's.

A similar, albeit slightly smaller, gap is observed between women and men incumbents (0.018). Providing additional support for our third set of hypotheses, that women members of the government party (H3a) and women incumbents (H3b) will use higher levels of positive sentiment in their campaign messages than men. With that being said, it is worth pointing out that women challengers are about as positive as men incumbents at the positivity level of 0.18. This further illustrates how women alter their behavior to be more positive, even when their challenger status would suggest they have fewer incentives to do so.

Next, we turn to the results for negative sentiment displayed in the right panel of Figure 2. First, we observe that members of the opposition engage in more negative sentiment than members
of the government. But there is important variation by candidate gender. The level of negative sentiment deployed by men from the opposition party is 0.087 compared to 0.081 for women from the opposition party. Interestingly, women's level of negative sentiment more closely resembles that of men from the government party. Still, women from the opposition party engage in more negative sentiment than women from the government. Thus, even though all opposition members have an incentive to engage in negative emoting, consistent with H 4 a , we observe that women do so less than men.

Finally, turning to the lower right panel we examine the difference between challengers and incumbents. Although we observe that on average, challengers are more negative than incumbents, there is not a significant challenger-incumbent gap for men. In other words, men incumbents use negative sentiment just as much as men challengers, indicating support for the idea that all candidates can benefit from negativity (Lau and Rovner 2009).

Nonetheless, women do not engage in negative emoting to the same extent as men. We find strong support for H4b: women challengers use less negative sentiment than men challengers. In fact, women challengers even use less negative sentiment than men incumbents, suggesting that gendered campaign dynamics exert more influence on women's behavior than does their challenger status.

Overall, the results show women are markedly less negative than men, suggesting that women confront a different set of campaign incentives. The gender gap is larger between men and women from the government party and incumbents-those candidates who have weaker incentives to send negative messages (about twice as large as that among members from the opposition party and challengers). But, of particular importance, the gender gap persists among opposition MPs and challengers-indicating that even when women's opposition/challenger status should compel them to use negative sentiment, they are less likely than men to do so. We contend that this is because
women face a double bind and are more likely than men to be met with negative reactions when they engage in negative emoting.

## Reactions to Men's and Women's Campaign Messages

We argued that women have a strategic incentive to behave in gender-typical ways to shield themselves from backlash on the campaign trail. Our primary analysis shows that women are, in fact, more likely than men to deploy positive sentiment in their messaging and to avoid negative sentiment. On the one hand, our results are consistent with our argument that women politicians are aware that they face competing expectations from voters-i.e., that politicians should exhibit masculine leadership traits, but women should display feminine, gender-typical traits (Schneider and Bos 2019; Bauer 2020). On the other hand, our results are observationally equivalent with the idea that women simply behave in more gender-typical ways because they are socialized to do so and not because they face different standards.

Our findings thus raise a second question: Are women met with adverse responses when they deploy negative sentiment? If women's negative emoting is met with similar reactions to men's, this indicates that women may be unnecessarily avoiding negative sentiment-a proven campaign strategy (Lau and Rovner 2009)—and their behavior may perhaps be better explained by gender socialization. Yet, if women are met with disproportionately negative reactions, then this suggests their behavior is a strategic attempt to traverse the double bind imposed on women candidates (Schneider and Bos 2014), and that women ultimately have one less tool in their campaign toolkit than men. Despite the importance of citizen's reactions to women's and men's use of emotional sentiment in their campaign messaging, we know very little about how citizens evaluate/react differently to men and women candidates in real world settings.

We derive two competing expectations from existing research. On the one hand, we may not expect women to elicit more negative responses from voters when they use negative sentiment. It is possible that women only avoid engaging in negative emoting because they are socialized to do so. A large body of work questions the assumption that voters respond differently to women candidates than to men. This research points to the conventional wisdom that when women run, they win, suggesting that women's underrepresentation in political office is better explained by lower levels of political ambition, than by voters' preferences (for a review, see Bernhard, Shames, and Teele 2021; Schneider et al. 2016). Meta analysis likewise finds a small bonus for women candidates when reviewing experimental research that examines voters' evaluations of men and women with the exact same profile (Schwarz and Coppock 2022). With respect to political arguments more specifically, evidence from survey experiments finds that voters from the UK evaluate men and women politicians similarly when they adopt a range of argument styles (Hargrave 2022). In particular, Hargrave finds that voters do not evaluate women more harshly when they display aggression. Evidence from women's participation during parliamentary debates likewise shows their speaking styles are similar to men's, suggesting that they now face less pressures-at least from other elitesto conform to stereotypically 'feminine’ communication styles (Hargrave and Blumenau 2022). Taken together, these findings suggest that women candidates are not evaluated differently than men. If anything, voters may prefer women candidates to men. These findings thus cast doubt on the idea that women who deploy negative sentiment will be met with different reactions than men.

On the other hand, there is reason to believe that women and men may be evaluated differently. Although voters may prefer women in some settings, the opposite may be true when they break with gender stereotypic behavior (Bauer 2021). Previous research, on communication with constituents, for instance, shows that women legislators tend to be evaluated more positively (negatively) than men when they provide high (low)-quality responses to constituents (Costa 2021).

Evaluations of men, by contrast, are less sensitive to the quality of their responses (Costa 2021). Other work shows women "face a disproportionate punishment for relying on negativity" during campaigns—but only when they are viewed as the instigator (Krupnikov and Bauer 2014, 167). Research on corruption illustrates a similar dynamic. Voters tend to favor women in context with high political corruption (Barnes and Beaulieu 2019), but when women themselves are accused of corruption, they are punished more harshly than corrupt men (Barnes, Beaulieu, and Saxton 2020). Combined, this work suggests society may hold women to different standards than men-rewarding women when they conform to gender stereotypes and punishing them when they fail to do so. This body of research leads us to posit that women candidates will elicit more negative emotions from voters when they use negative sentiment, and more positive emotions when they emote positively.

To assess these competing expectations, and better understand whether women have a strategic incentive to adopt more positive and less negative sentiment to avoid reprisal from constituents-or whether they simply use more positive and less negative sentiment than men because they are socialized to do so-we evaluate the following hypothesis:

H5: Campaign messages containing positive/ negative sentiment from women candidates will be met with more positive/ negative responses, than similar messages from men.

## Evaluating Reactions to Women's and Men's Campaign Messaging

To evaluate reactions to women and men candidates, we look at Twitter replies to the candidates' tweets used in the previous analysis. The use of observational data from responses to real candidates in the run up to elections is an important advancement in political science research. Indeed, although there is copious research examining how subjects respond to experimental manipulations of the gender of hypothetical candidates, with very few exceptions (e.g., Boussalis et al. 2021) we do not know how voters respond to positive and negative sentiment from real candidates. This is an important distinction because experimental research evaluates subjects' responses to identical men
and women candidate profiles in hypothetical settings. It does not account for the fact that in practice men and women candidates do not have identical traits and characteristics and that voters tend to prefer traditional [men] profiles (Teele, Kalla, and Rosenbluth 2018). Analyzing Twitter replies thus offers unique insights into citizens' responses to actual campaign sentiment.

We start with the dataset from the previous analysis as a foundation to build a second dataset that consists of responses to the candidate tweets. We collected this sample of tweets through the "follow" functionality of the Twitter Streaming API. This allows API users to supply a list of Twitter user IDs and receive a stream of tweets related to these accounts, including the tweets originating from these accounts and replies, likes, and retweets. This approach results in 1,324,175 responses to the original set of tweets generated by candidates.

Notably, responses are not equally distributed across original tweets. Specifically, simple descriptive statistics show that negative candidate tweets tend to attract far more attention than positive candidate tweets. Whereas a tweet above the median level of positivity garners about 7.8 replies, tweets above the median level of negativity attract about 10.2 replies. The difference between the two is statistically significant at the $99.9 \%$ level. Moreover, these trends are similar for both men and women candidates (albeit men's tweets receive, on average, slightly more responses than women's tweets). The fact that negative tweets attract more responses helps to illustrate why candidates have an incentive to use negativity in tweets. Consistent with research from Marcus, Neuman, and MacKuen (2000), we observe that negative emotional appeals make people more attentive to candidates' tweets. So, the puzzle remains as to why women candidates are more likely to avoid tweeting negatively than their men counterparts, even though negative tweets attract more attention for both genders.

Next, to solve this important puzzle and test our hypothesis (H5), we analyze the data using the same approach described above to quantify the level of positive and negative sentiment in each
of the replies, using the Harvard IV dictionary. The dependent variables are the positive and negative sentiments expressed in the replies. The average positive (negative) score is 0.13 ( 0.11 ) on this scale with a standard deviation of 0.13 (0.13). As it turns out, overall positivity is higher in candidate tweets than in replies to them, while the negativity tends to be lower in candidate tweets than in replies to them. That is, candidate tweets are generally more positive and less negative than the feedback they receive.

As in the previous section, we estimate a series of regression models that take the measure of positive and negative sentiment of replies as their outcomes. In this analysis, the unit of observation is a reply to the candidate tweets. There are two main independent variables regarding the original tweets they were replying to. The first is the candidate gender. The variable Woman takes on a value of 1 for women candidates and 0 for men candidates. Second, we account for the sentiment expressed in the original tweet. The variable Candidate Positivity is used to measure the magnitude of positive sentiment in the candidate's original tweet; similarly, Candidate Negativity is used to measure the degree of negative sentiment in the candidate's original tweet. Recall that positivity and negativity are two separate measures, each ranging from 0 to 1 where 0 is neutral and 1 is the strongest level of sentiment.

We estimate two sets of models, one evaluating the positivity of replies and the other evaluating the negativity of replies. Overall, we anticipate that Candidate Positivity will be positively associated with reply positivity and Candidate Negativity will be positively associated with reply negativity. Beyond these direct effects, we are evaluating the hypothesis that women's emotive tweets will be met with stronger sentiment in the replies. Specifically, when women candidates are positive, they will elicit more positive reactions than men, but when they are negative, they will be met with even more negativity than men. Thus, for each set of models, we first evaluate the direct effect of the main independent variables-the gender of the candidate and the positivity/negativity
of the tweet. Then, we include two-way interactions between candidate gender and the positivity/negativity of their original tweet to assess if women and men candidates elicit different responses. The models also include the same set of control variables as in the previous analysis. We cluster standard errors by the tweet ID of the candidate tweet-i.e., the level of the treatment assignment in this research design.

## Analysis of Replies to Candidate Tweets

Figure 3 plots the results for the reply sentiment analysis (Appendix Table B.2). It is evident from the coefficient on Candidate Positivity (left panel), that as the level of positivity in candidate tweets increases so too does the level of positivity in replies to these tweets. A similar, albeit slightly stronger relationship is observed between Candidate Negativity and the level of Reply Negativity (right panel). For one standard deviation increase in the positivity (negativity) level of the candidate's tweet, the positivity (negativity) level of the corresponding replies increases by 0.012 ( 0.011 ). These relationships are consistent with expectations from previous research that suggests politicians and political parties use sentiment to elicit emotional responses from voters.

Next, it is clear from the positive and significant coefficient for Woman, in the models without interaction terms (circles) that, all else equal, women candidates elicit stronger emotional replies than do men. They are met with both more positive and more negative replies than are men. Although it is notable that women, regardless of their actions, draw out more emotive replies, we are interested in the interaction between candidate gender and the sentiment of their original tweet for evaluating H5. We thus turn to the interaction between Woman and Candidate Positivity/Negativity plotted with triangles in Figure 3 (available in Appendix Table B. 2 Models 2 and 4).


- (1) No
(2) Yes

Note: Dependent variable for the left panel is the level of positivity in replies; the right panel is the level of negativity. Model 1 in each panel has no interactions (circles), and Model 2 includes interactions (triangle).
Figure 3: Regression Coefficients for the Reply Sentiment Models

The interaction effects between Woman and Positivity/Negativity are positive and significant, indicating support for our expectation that citizens respond more positively to women when they use positive sentiment and more negatively when they engage in negative emoting. The magnitude of the relationship, however, differs substantially depending on whether women are deploying
positive or negative sentiment. Specifically, the size of the coefficient for the negativity model (0.055) is more than five times larger than for the positivity model (0.009).

To illustrate the magnitude of this relationship, we plot the expected values for reply tweet positivity (left) and negativity (right) in Figure 4. Looking first at positivity, in the panel on the left we plot the expected level of Candidate Positivity on the x -axis, and positivity in reply to tweets on the y -axis. The results indicate that the baseline response to women candidates (when Candidate Positivity is at 0 ) is more positive than the baseline response to men, indicating that, on average, people respond more positively to women candidates than to men. For both women and men, as Candidate Positivity increases so does citizen positivity, showing that all candidates are met with more positive emoting when they use more positive sentiment in their tweets. Importantly, however, women are met with even more positive responses than are men for the same level of positive sentiment. This is evident from the steeper slope on the line for women as compared to men. The left panel in Figure 4 thus provides support for our expectations that positive sentiment in women's campaign messaging will be met with more positivity than similar messages from men.

Next, turning to candidate negativity, the panel on the right plots the expected level of Candidate Negativity on the x -axis against the expected level of negativity in reply tweets on the y -axis. Here again the intercept for women candidates is higher indicating that women elicit more emotive responses regardless of the level of sentiment deployed by the original candidate tweet. Furthermore, the positive and significant slope on the line for women and men candidates indicate that increases in negative sentiment from both women and men candidates are met with more negativity in replies. As compared to the figure on the left (positivity), two trends stand out. First, the relationship between candidate negativity and reply negativity is much steeper for both men and women. This indicates that the use of negative sentiment elicits stronger reactions than does the use of positive sentiment. Second, the difference in the slope for men and women candidates is more
pronounced. Although the difference between the slope for positivity in the left panel is statistically different for women and men, the difference in the slope is quite modest. For negativity, however, it is clear that women are met with much stronger reactions than are men. In fact, the relationship between negative tweets and reply negativity is about $50 \%$ steeper for women than for men, indicating that campaign messages containing negative sentiment from women candidates elicit more negative responses, than similar messages from men. Combined the results presented in Figures 3 and 4 show support for the hypothesis that women are rewarded more than men for positive emoting but punished more than men for negative emoting (H5).


Note: The plot shows the predicted level of sentiment—Positivity (left) and Negativity (right)---in replies to candidate tweets across gender of replied tweet authors (i.e., the candidate's gender). The predictions are generated from models with interaction terms, Models (2) and (4) in Figure 3. The gender of the replied tweet authors is indicated by the color of the prediction lines (gray: woman, black: men). The shaded areas denote $95 \%$ confidence intervals.

## Figure 4: Predicted Levels of Sentiment in Replies to Candidate Tweets

It is possible, of course, that reply negativity is just a product of candidate supporters pilingon and not indicative of citizens being more critical of (or negative toward) the candidate who originated the tweet. To further probe whether negativity in replies reflect backlash against women
candidates who break with gender stereotypes, as posited above (H5), we consider whether citizens are "favoriting"/"liking" and replying to negative tweets by women and men at similar rates. To do this, we assess two sets of models, one that uses the number of likes as the dependent variable, and a second set that takes the number of replies as the dependent variable. As in the previous analysis, we consider the level of positivity/negativity in the original tweet and assess whether tweets are associated with more likes as positivity/negativity increases. We control for the same set of covariates as in the previous analysis, but because we are examining the number of likes/replies, we use a Poisson count model (Appendix Tables B. 3 and B.4).

Figure 5 shows how the estimated number of likes given to a candidate's tweet varies depending on the candidate's gender and the sentiment of the content of the tweet. First, we observe that all tweets by women, regardless of the level of positivity/negativity, garner fewer likes than tweets by men. Second, tweet positivity is associated with fewer likes for both men and women—suggesting that positive tweets do not garner as much attention as negative ones. As positivity increases, the number of likes decreases.

With respect to negativity, by contrast, as negativity increases so does the number of likes a tweet garners. That said, negative tweets by women attract far fewer likes than do negative tweets by men. And, as negativity increases, the gap between the number of likes men garner and the number of likes for women increases. Whereas men's tweets see an average of 22.7 . likes when negativity is at 95 percentile, women's tweets only garner about 8.7 likes, suggesting that citizens are more likely to support or approve of negative tweets from men than from women. Seeing as how the reply sentiment to negative tweets is much more negative for women than for men, this striking difference suggests that negative replies to women's negative tweets may not simply be a product of supporters piling-on and instead may reflect disapproval of tweet negativity from women candidates.


Note: The plot shows the predicted number of likes given to candidate tweets across gender of liked tweet authors (i.e., the candidate's gender). The predictions are generated from the model in Appendix Table B.3. The gender of the liked tweet authors is indicated by the color of the prediction lines (gray: woman, black: men). The shaded areas denote $95 \%$ confidence interval
Figure 5: Predicted Number of Likes to Candidate Tweets

Importantly, it is not the case that negative tweets by women get fewer likes than men's
because women's tweets simply receive less attention. As a matter of fact, when we examine how many responses women's and men's tweets received, we observe that the most negative tweets from women garner just as many responses as the most negative tweets from men. Figure 6 shows how the estimated number of replies to a candidate's tweet varies depending on the candidate's gender and the sentiment of the candidate's original tweet. The figure indicates that whereas women's positive (and neutral) tweets garner less responses than men's, men's and women's negative tweets solicit similar levels of responses. In fact, when tweet negativity is low there is a gender gap, wherein tweets from men get more responses. But, as tweets become more negative, the gender gap in the number of replies disappears entirely. The similar numbers in tweet replies (Figure 6) combined with the higher level of negativity in replies (Figure 4) and smaller number of likes (Figure 5) lend further
evidence in support of the idea that negative tweets from women candidates are not as well received as negative tweets from men candidates.


Note: The plot shows the predicted number of replies to candidate tweets across gender of replied tweet authors (i.e., the candidate's gender). The predictions are generated from the model in Appendix Table B.4. The gender of the replied tweet authors is indicated by the color of the prediction lines (gray: woman, black: men). The shaded areas denote $95 \%$ confidence intervals.

## Figure 6: Predicted Number of Replies to Candidate Tweets

Combined, these findings are consistent with our expectation that women engage in strategic behavior on the campaign trail. Specifically, we argued that if women's behavior is strategic, and not simply a product of gendered socialization, we should observe evidence of backlash when they engage in negative emoting. Through the analysis of replies, we observe that although negative emoting is always met with negative responses, women are met with more negativity than men when they engage in negative emoting. And, even though the most negative tweets by women attract just as many responses as tweets from men, in contrast to men, they attract far fewer likes. These two factors suggest that the negative sentiment in replies is not simply a product of supporters reinforcing the negativity from the original tweet. Instead, the negativity in replies to women candidates is likely to reflect-at least in part-negativity aimed at the candidate (or at least their
message). Our results are thus consistent with the idea that women strategically avoid negative sentiment to avoid backlash on Twitter and that this behavior is not just a product of socialization.

## Conclusions

Candidates have a range of available tools to help them navigate campaigns. Emotive language is useful for motivating voters to support the status quo and for invoking scrutiny, causing voters to question candidates' positions and qualifications. Yet no study to date has examined how women and men candidates may use these tools differently during campaigns. Using data from 2,662 candidates across two British elections, we show that despite incentives fostered by candidates' government and incumbency status, women candidates are markedly more likely to deploy positive sentiment and less likely to use negativity in their campaign rhetoric. Furthermore, we show that when women do use negative sentiment, they are more likely than men to be met with negative reactions from the public. In doing so, we contribute to a burgeoning body of research that demonstrates how leaders use political messages to strategically elicit emotions (Crabtree et al. 2021) and appeal directly to voters (Osnabrügge, Hobolt, and Roden 2021).

That women candidates are more likely to engage in positive emoting and are met with more negative responses than men for negative emoting have important implications for women politicians, campaign strategies, and our understanding of how emotive rhetoric influences voters. When taken at face value, that women's positive campaign messages are met with more positive responses suggest that women can effectively navigate the double bind by leaning into gender-typical roles and deploying positive sentiment. This strategy has the added benefit of allowing them to avoid reprisal from voters and observers by eschewing negativity. But, upon closer inspection, it is clear that the double bind limits women's range of available campaign strategies. Going negative has long been seen as a useful approach when candidates are in tight elections (Druckman, Kifer, and

Parkin 2010). The fact that this strategy is not as available to women means they may be disproportionately disadvantage in close races. More generally, it demonstrates that women do not benefit from the same campaign strategies as men.

Importantly, this limitation constrains all women candidates. Members of the opposition and challengers may be best situated to benefit from negative emoting, but in some circumstances even government and incumbent candidates have an incentive to use negative sentiment. Negativity is an invaluable tool for candidates looking to disrupt the status quo and to challenge voters to closely scrutinize candidates. Consistent with this, our analysis shows that men incumbents are about as likely as men challengers to use negative sentiment. And, men from the government party do so as frequently as opposition women. If women are not able to successfully use negative sentiment, it suggests that all women, even incumbents and members of the government, have fewer tools for navigating the electoral terrain. This finding illustrates the classic double bind for women (Bos and Schneider 2014). Whereas negativity can help the average male candidate accomplish a number of goals, women are disproportionately punished for deploying negative sentiment.

Our findings may also have implications for parliamentary deliberations and government accountability. The parliament is the primary institution responsible for monitoring the government. Thus, a key part of MPs' jobs is to scrutinize and challenge the government's work. Our results suggest that when women engage in negative rhetoric, they are evaluated more harshly than men. If this same dynamic plays out when women criticize the government, it may disincentivize accountability among women MPs, for fear of losing support at the polls. And, for women who are not deterred, it may disproportionately threaten their electoral fortunes. Future research should examine whether voters differentially evaluate men and women MPs who publicly scrutinize the government during oral question times, on social media, and in the news to better understand how gendered evaluations influence women's ability to effectively perform their job. Moreover, to better
understand how women are adjusting their behavior to navigate different political settings, future work should consider whether women MPs use different rhetoric in high-visibility settings (e.g., debates on high-profile issues or comments on social media) than in low-visibility settings where they are less likely to be viewed by voters.

Finally, in addition to showing that women are more constrained during campaigns, our research contributes to growing evidence of an increasingly uncivil and hostile political environment for women (Rheault, Rayment, and Musulan 2019). That women's negative emoting elicits more negative responses than men's offers additional evidence of the broader phenomenon wherein women are increasingly more likely to be confronted with hostility, harassment, and incivility in politics (Collignon and Wolfgang 2020), and particularly in online political spaces (Rheault, Rayment, Musulan 2019). Though our research does not measure incivility directly, it offers additional systematic evidence of the ways women politicians experience campaigns differently than men, ultimately forcing them to "pay a higher price for power" (Håkansson 2021, 515).

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## Online Appendix

## Appendix A. Descriptive Statistics

Appendix A describes how candidates use Twitter, with a focus on variation across our key explanatory variables. Tables A.1-A. 3 shows the number of candidates with Twitter accounts by party (A.1), incumbency status (A.2), and gender (A.3). It is evident from the Table A. 1 that candidates from the governing party (in both years the Conservative Party) are less likely to have Twitter accounts compared to candidates from other parties (except for the UKIP candidates). Table A. 2 shows that the trend for incumbent candidates is the opposite of that for government candidates. MPs, as opposed to challengers, are more likely to have a Twitter account. Next, Table A. 3 shows women are more likely to have Twitter accounts, especially in the 2017 election ( 77.3 percent in 2017; 86.1 percent in 2019) than men ( 67.4 percent in 2017; 86.1 percent in 2019).

To assess the volume of content generated by different candidates, Table A. 4 shows the mean number of tweets by government/opposition, incumbency status, and gender. Government candidates post fewer messages ( 32.8 in 2017; 37.9 in 2019) than do opposition candidates (49.0 tweets in 2017; 61.1 in 2019). Incumbents generate more tweets than challengers (averaging 65.6 vs. 37.6 in 2017; 78.8 vs. 47 in 2019). Woman candidates are more likely to generate tweets during the campaign than men, with a higher average number of tweets ( 55.0 vs. 40.2 in 2017; 66.4 vs. 48.1 in 2019).

Table A.1: Candidates with Twitter accounts (by party)

| Election | Party | Count | Prop Has Twitter |
| :---: | :---: | :---: | :---: |
| 2017 | Conservative | 653 | 0.743 |
| 2017 | Labour | 686 | 0.848 |
| 2017 | Liberal Democrat | 644 | 0.691 |
| 2017 | Scottish National Party | 61 | 0.984 |
| 2017 | UK Independence Party | 384 | 0.354 |
| 2019 | Conservative | 635 | 0.850 |
| 2019 | Labour | 646 | 0.930 |
| 2019 | Liberal Democrat | 611 | 0.876 |
| 2019 | Scottish National Party | 59 | 1.000 |
| 2019 | UK Independence Party | 44 | 0.341 |
| 2019 | Brexit Party | 275 | 0.840 |

Table A.2: Candidates with Twitter accounts (by incumbency status)

| Election | Incumbency | Count | Prop Has <br> Twitter |
| :---: | :---: | :---: | :---: |
| 2017 | 0 | 1,821 | 0.650 |
| 2017 | 1 | 607 | 0.865 |
| 2019 | 0 | 1,729 | 0.852 |
| 2019 | 1 | 541 | 0.939 |
|  |  |  |  |

Table A.3: Candidates with Twitter accounts (by gender)

| Election | Gender | Count | Prop Has <br> Twitter |
| :---: | :---: | :---: | :---: |
| 2017 | Women | 726 | 0.773 |
| 2017 | Men | 1,702 | 0.674 |
| 2019 | Women | 807 | 0.895 |
|  |  | 1,463 | 0.861 |

Table A.4: Twitter activity
A. 4 (a): By government and opposition

| Election | Government | Prop Active | Mean N Tweets |
| :---: | :---: | :---: | :---: |
| 2017 | 0 | 0.624 | 49.0 |
| 2017 | 1 | 0.640 | 32.8 |
| 2019 | 0 | 0.830 | 61.1 |
| 2019 | 1 | 0.787 | 37.9 |

A. 4 (b): By incumbency

| Election | Status | Prop Active | Mean N Tweets |
| :---: | :--- | :---: | :---: |
| 2017 | Challenger | 0.571 | 37.6 |
| 2017 | Incumbent | 0.801 | 65.6 |
|  |  |  |  |
| 2019 | Challenger | 0.794 | 47.0 |
|  | Incumbent | 0.895 | 78.8 |

A. 4 (c): By gender

| Election | Gender | Prop Active | Mean N Tweets |
| :---: | :---: | :---: | :---: |
| 2017 | Women | 0.708 | 55.0 |
| 2017 | Men | 0.594 | 40.2 |
| 2019 | Women | 0.856 | 66.4 |
|  |  |  |  |
| 2019 | Men | 0.797 | 48.1 |
|  |  |  |  |

Table A.5: Average sentiment by groups
A. 5 (a): By government and opposition

| Election | Government | Avg Pos | Avg Neg |
| :---: | :---: | :---: | :---: |
| 2017 | 0 | 0.182 | 0.084 |
| 2017 | 1 | 0.200 | 0.075 |
| 2019 | 0 | 0.188 | 0.083 |
| 2019 | 1 | 0.203 | 0.072 |
|  |  |  |  |

A. 5 (b): By incumbency

| Election | Status | Avg Pos | Avg Neg |
| :---: | :--- | :---: | :---: |
| 2017 | Challenger | 0.180 | 0.083 |
| 2017 | Incumbent | 0.201 | 0.078 |
|  |  | 0.189 | 0.081 |
| 2019 | Challenger |  |  |
|  |  | 0.201 | 0.078 |
|  | Incumbent |  |  |

A. 5 (c): By gender

| Election | Gender | Avg Pos | Avg Neg |
| :---: | :---: | :---: | :---: |
| 2017 | Women | 0.198 | 0.076 |
| 2017 | Men | 0.182 | 0.084 |
| 2019 | Women | 0.200 | 0.078 |
|  |  | 0.187 | 0.081 |
| 2019 | Men |  |  |

Appendix B: Full Regression Tables

Table B.1: Regression Coefficients for the Candidate Tweet Sentiment Models (Figure 1, Full-model)

|  | DV: Positivity |  |  | DV: Negativity |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| Woman | $\begin{aligned} & 0.016^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.015^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.015^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.007^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.006^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.005^{* * *} \\ & (0.001) \end{aligned}$ |
| Government | $\begin{aligned} & 0.010^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.009^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.010^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.006^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.005^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.007^{* * *} \\ & (0.001) \end{aligned}$ |
| Incumbent MP | $\begin{aligned} & 0.016^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.017^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.015^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.003^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.003^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.000 \\ & (0.001) \end{aligned}$ |
| Woman x Government |  | $\begin{aligned} & 0.004^{*} \\ & (0.002) \end{aligned}$ |  |  | $\begin{aligned} & -0.005^{* * *} \\ & (0.001) \end{aligned}$ |  |
| Woman x Incumbent |  |  | $\begin{aligned} & 0.003 \\ & (0.002) \end{aligned}$ |  |  | $\begin{aligned} & -0.006^{* * *} \\ & (0.001) \end{aligned}$ |
| South East | $\begin{aligned} & -0.007^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.007^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.007^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.005^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.005^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.005^{* * *} \\ & (0.001) \end{aligned}$ |
| South East | $\begin{aligned} & -0.007^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.007^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.007^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.005^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.005^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.005^{* * *} \\ & (0.001) \end{aligned}$ |
| (Region) East Midlands | $\begin{aligned} & 0.009^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.009^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.008^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.009^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.009^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.009^{* * *} \\ & (0.001) \end{aligned}$ |
| (Region) London | $\begin{aligned} & 0.001 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.001 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.001 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.001 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.001 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.001 \\ & (0.001) \end{aligned}$ |
| (Region) North East | $\begin{aligned} & -0.011^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.011^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.011^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.000 \\ & (0.002) \end{aligned}$ |
| (Region) North West | $\begin{aligned} & -0.001 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.001 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.001 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.000 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.000 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.001 \\ & (0.001) \end{aligned}$ |
| (Region) Northern Ireland | $\begin{aligned} & -0.015^{* * *} \\ & (0.004) \end{aligned}$ | $\begin{aligned} & -0.014^{* * *} \\ & (0.004) \end{aligned}$ | $\begin{aligned} & -0.015^{* * *} \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.004 \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.004 \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.004 \\ & (0.003) \end{aligned}$ |
| (Region) Scotland | $\begin{aligned} & -0.009^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.010^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.009^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.007^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.006^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.007^{* * *} \\ & (0.001) \end{aligned}$ |
| (Region) South West | $\begin{aligned} & 0.002 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.002 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.002 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.002 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.002 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.002 \\ & (0.001) \end{aligned}$ |
| (Region) Wales | $\begin{aligned} & -0.006^{* *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.006^{* *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.006^{* *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.014^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.014^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.014^{* * *} \\ & (0.001) \end{aligned}$ |
| (Region) West Midlands | $\begin{aligned} & 0.002 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.002 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.002 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.001 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.002 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.001 \\ & (0.001) \end{aligned}$ |
| (Region) Yorkshire and The Humber | $\begin{aligned} & -0.002 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.002 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.002 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.002 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.002 \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.002 \\ & (0.001) \end{aligned}$ |
| Election Year | $\begin{aligned} & 0.004^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.004^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.004^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.000) \end{aligned}$ |
| Intercept | $\begin{aligned} & -8.343^{* * *} \\ & (0.742) \\ & \hline \end{aligned}$ | $\begin{aligned} & -8.401^{* * *} \\ & (0.742) \\ & \hline \end{aligned}$ | $\begin{aligned} & -8.383^{* * *} \\ & (0.742) \\ & \hline \end{aligned}$ | $\begin{aligned} & 0.804 \\ & (0.517) \end{aligned}$ | $\begin{aligned} & 0.872 \\ & (0.517) \end{aligned}$ | $\begin{aligned} & 0.888 \\ & (0.517) \\ & \hline \end{aligned}$ |
| $\mathrm{R}^{2}$ | 0.008 | 0.008 | 0.008 | 0.003 | 0.003 | 0.003 |
| Adj. $\mathrm{R}^{2}$ | 0.008 | 0.008 | 0.008 | 0.003 | 0.003 | 0.003 |
| Num. obs. | 164784 | 164784 | 164784 | 164784 | 164784 | 164784 |
| RMSE | 0.147 | 0.147 | 0.147 | 0.103 | 0.103 | 0.103 |

${ }^{* * *} \mathrm{p}<0.001 ;{ }^{* *} \mathrm{p}<0.01 ;{ }^{*} \mathrm{p}<0.05$

Table B.2: Regression Coefficients for the Reply Sentiment Models (Figure 3, Full-model)

|  | DV: Reply Positivity |  | DV: Reply Negativity |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) |
| Woman | $\begin{aligned} & 0.008^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.007^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.008^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.001^{* * *} \\ & (0.000) \end{aligned}$ |
| Candidate Positivity | $\begin{aligned} & 0.077^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.075^{* * *} \\ & (0.001) \end{aligned}$ |  |  |
| Candidate Negativity |  |  | $\begin{aligned} & 0.109^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.096^{* * *} \\ & (0.001) \end{aligned}$ |
| Woman x Positivity |  | $\begin{aligned} & 0.009^{* * *} \\ & (0.002) \end{aligned}$ |  |  |
| Woman x Negativity |  |  |  | $\begin{aligned} & 0.055^{* * *} \\ & (0.003) \end{aligned}$ |
| Incumbent MP | $\begin{aligned} & -0.022^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.023^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.016^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.016^{* * *} \\ & (0.000) \end{aligned}$ |
| Government | $\begin{aligned} & -0.009^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.009^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.008^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.008^{* * *} \\ & (0.000) \end{aligned}$ |
| Election Year | $\begin{aligned} & -0.006^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.006^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.003^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.003^{* * *} \\ & (0.000) \end{aligned}$ |
| Intercept | $\begin{aligned} & 12.479^{* * *} \\ & (0.281) \\ & \hline \end{aligned}$ | $\begin{aligned} & 12.398^{* * *} \\ & (0.281) \\ & \hline \end{aligned}$ | $\begin{aligned} & 5.665^{* * *} \\ & (0.255) \\ & \hline \end{aligned}$ | $\begin{aligned} & 5.697^{* * *} \\ & (0.255) \\ & \hline \end{aligned}$ |
| $\mathrm{R}^{2}$ | 0.014 | 0.014 | 0.014 | 0.014 |
| Adj. $\mathrm{R}^{2}$ | 0.014 | 0.014 | 0.014 | 0.014 |
| Num. obs. | 1286466 | 1286466 | 1286466 | 1286466 |
| RMSE | 0.134 | 0.134 | 0.125 | 0.125 |

${ }^{* * *} \mathrm{p}<0.001 ;{ }^{* *} \mathrm{p}<0.01 ;{ }^{*} \mathrm{p}<0.05$

Table B.3: Coefficients for the Favorite Count Model

|  | Model |
| :--- | :--- |
| Woman | $-0.986^{* * *}$ |
|  | $(0.001)$ |
| Candidate Positivity | $-0.359^{* * *}$ |
|  | $(0.002)$ |
| Candidate Negativity | $2.249^{* * *}$ |
|  | $(0.002)$ |
| Woman x Positivity | $-0.221^{* * *}$ |
|  | $(0.004)$ |
| Woman x Negativity | $0.223^{* * *}$ |
|  | $(0.005)$ |
| Incumbent MP | $3.285^{* * *}$ |
|  | $(0.001)$ |
| Government | $-0.914^{* * *}$ |
|  | $(0.001)$ |
| Election Year | $0.676^{* * *}$ |
|  | $(0.000)$ |
| Intercept | $-1361.041^{* * *}$ |
|  | $(0.675)$ |
| Deviance | 74405942.808 |
| Num. obs. | 164784 |
| ${ }^{* * *} \mathrm{p}<0.001 ;{ }^{* *} \mathrm{p}<0.01 ;{ }^{*} \mathrm{p}<0.05$ |  |

Table B.4: Coefficients for the Reply Count Model

|  | Model 1 |
| :---: | :---: |
| Woman | $\begin{aligned} & -0.032^{* * *} \\ & (0.008) \end{aligned}$ |
| Candidate Positivity | $\begin{aligned} & -0.266^{* * *} \\ & (0.019) \end{aligned}$ |
| Candidate Negativity | $\begin{aligned} & 0.699^{* * *} \\ & (0.029) \end{aligned}$ |
| Woman x Positivity | $\begin{aligned} & -0.104^{* * *} \\ & (0.027) \end{aligned}$ |
| Woman x Negativity | $\begin{aligned} & -0.032 \\ & (0.045) \end{aligned}$ |
| Incumbent MP | $\begin{aligned} & 0.806^{* * *} \\ & (0.007) \end{aligned}$ |
| Government | $\begin{aligned} & 0.417^{* * *} \\ & (0.007) \end{aligned}$ |
| South East | $\begin{aligned} & -0.131^{* * *} \\ & (0.008) \end{aligned}$ |
| South East | $\begin{aligned} & -0.131^{* * *} \\ & (0.008) \end{aligned}$ |
| (Region) East Midlands | $\begin{aligned} & -0.080^{* * *} \\ & (0.010) \end{aligned}$ |
| (Region) London | $\begin{aligned} & 0.118^{* * *} \\ & (0.010) \end{aligned}$ |
| (Region) North East | $\begin{aligned} & -0.177^{* * *} \\ & (0.012) \end{aligned}$ |
| (Region) North West | $\begin{aligned} & -0.151^{* * *} \\ & (0.009) \end{aligned}$ |
| (Region) Northern Ireland | $\begin{aligned} & -0.072^{* * *} \\ & (0.021) \end{aligned}$ |
| (Region) Scotland | $\begin{aligned} & -0.158^{* * *} \\ & (0.009) \end{aligned}$ |
| (Region) South West | $\begin{aligned} & -0.143^{* * *} \\ & (0.009) \end{aligned}$ |
| (Region) Wales | $\begin{aligned} & -0.283^{* * *} \\ & (0.010) \end{aligned}$ |
| (Region) West Midlands | $\begin{aligned} & -0.153^{* * *} \\ & (0.009) \end{aligned}$ |
| (Region) Yorkshire and The Humber | $\begin{aligned} & -0.130^{* * *} \\ & (0.009) \end{aligned}$ |
| Election Year | $\begin{aligned} & 0.128^{* * *} \\ & (0.002) \end{aligned}$ |
| Intercept | $\begin{aligned} & -256.924^{* * *} \\ & (4.459) \end{aligned}$ |
| $\mathrm{R}^{2}$ | 0.208 |
| Adj. $\mathrm{R}^{2}$ | 0.207 |
| Num. obs. | 164784 |
| RMSE | 0.877 |

${ }^{* * *} \mathrm{p}<0.001 ;{ }^{* *} \mathrm{p}<0.01 ;{ }^{*} \mathrm{p}<0.05$

# Appendix C: Example tweets 

Positive (Score: 0.8), Female, Government, Challenger

DrFionaFawcett
@DrFionaCares

## Thank you Liz. And thank you for your help and support x

Liz Smith @mspliz • Dec 11, 2019
Wishing all @ScotTories candidates all the very best tomorrow.

6:01 PM • Dec 11, 2019 • Twitter for iPhone

Positive (Score: 0.71), Male, Opposition (Labour), Incumbent

## Massive thanks for your kind support. It means a great deal.

, Same Difference @SameDifferenc17 • Dec 11, 2019
Same Difference would like to wish @KarlTurnerMP all the best in tomorrows General Election.

Karl Turner is a fantastically commited and proud community MP and has supported so many people in our local area; in particular the most vulnerable in our society.
Good luck, Karl.


9:22 PM • Dec 11, 2019 • Twitter for iPhone

Negative (Score: 1.0), Male, Government, Challenger


Peter Fortune AM *
@PeterTFortune

## This is getting silly....

4. Channel 4 News @Channel4News • Dec 6, 2019

Boris Johnson says "people of talent" not "people of colour."
Our earlier tweet was a mistake. We misheard and we apologise.

1:01 PM • Dec 6, 2019 • Twitter for iPhone

Negative (Score: 1.0), Female, Opposition (Labour), Challenger

## How utterly embarrassing and desperate.

Angela Rayner @AngelaRayner • Nov 28, 2019
This is embarrassing ${ }^{\bullet}$ don't pick on me or I'll send in me mate and dad. I truly cannot understand why anyone would want to make Boris Johnson Prime Minister - I mean we didn't get a vote the first time! The power is yours electorate, 5 years of this? twitter.com/bendepear/stat...

12:18 AM • Nov 29, 2019 • Twitter for iPhone


[^0]:    ${ }^{1}$ https://democracyclub.org.uk/
    ${ }^{2}$ Appendix Tables A.1-A. 3 shows the number of candidates with Twitter accounts by party (A.1), incumbency status (A.2), and gender (A.3).
    ${ }^{3}$ Appendix Table A. 4 shows the mean number of tweets by government/opposition, incumbency status, and gender.

[^1]:    ${ }^{4}$ For illustrative purposes Appendix C shows examples of tweets with varying levels of positivity and negativity.

