Pitch Perfect: Vocal Pitch and the Emotional Intensity of Congressional Speech*

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Abstract

Though audio archives are available for a number of political institutions, the data they provide receive scant attention from researchers. Yet, audio data offer important insights, including information about speakers' emotional states. Using one of the largest collections of natural audio ever compiled—74,158 Congressional floor speeches—we introduce a novel measure of legislators' emotional intensity: small changes in vocal pitch that are difficult for speakers to control. Applying our measure to MCs' floor speeches about women, we show that female MCs speak with greater emotional intensity when talking about women as compared to both their male colleagues and their speech on other topics. Our two supplementary analyses suggest that increased vocal pitch is consistent with legislators' broader issue commitments, and that emotionally intense speech may affect other lawmakers' behavior. More generally, by demonstrating the utility of audio-as-data approaches, our work highlights a new way of studying political speech.

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The analysis of increasingly vast stores of text data has transformed political science research. Scholars have used text-as-data approaches to shed new light on existing questions in American politics, comparative politics, and international relations, and to open new lines of inquiry across these subfields (Grimmer, 2013; Laver, Benoit and Garry, 2003; King and Lowe, 2003; Gerner et al., 1994; Hopkins and King, 2010). The impact of these methods has been especially pronounced in the study of legislative politics both in the United States (e.g., Quinn et al., 2010) and abroad (e.g., Proksch and Slapin, 2012). Though the development of sophisticated automated techniques for treating text as data has unlocked new and interesting sources of political information (Grimmer and Stewart, 2013), to date this work has largely neglected audio data, which is stripped away in transcription. Yet, audio data contains information about an important component of (political) speech: speakers' non-verbal expressions.

In this paper, we posit that it is not only what legislators say that matters, but also how they say it. Drawing on well-established psychology research on emotions and vocal communication, we argue that speakers' emotional intensity is reflected in minor changes in vocal pitch that are difficult to control. We assess this claim using one of the largest collections of natural audio ever compiled – all U.S. House floor speeches given over a five-year period. With this previously untapped resource, we construct a novel measure of legislators' emotional intensity based on small deviations above or below a speaker's baseline vocal pitch. Coupled with corresponding text data, our measure allows for the examination of legislators' emotional intensity around different issue areas. By reincorporating audio data, we thus offer a promising new addition to existing methods of studying text as data, especially within research on legislatures.

To develop and test our approach, we examine female House members' speech on behalf of women. Women remain significantly underrepresented in the U.S. Congress. Legislative speech, in turn, is especially meaningful for historically marginalized groups. As well as fostering feelings of institutional trust (Mansbridge, 1999), speech facilitates the link between numeric (or descriptive) and policy (or substantive) representation. Whether it is talking more about women (Pearson and Dancey, 2011*b*) or "women's issues" (Gerrity, Osborn and Mendez, 2007; Osborn and Mendez, 2010), scholars have consistently shown that female representatives are more likely to elevate the voice of women both within (Pearson and Dancey, 2011*a*) and beyond the halls of government (Herrnson, Lay and Stokes, 2003). Because female MCs have a demonstrated commitment to representing women, this issue area serves as an ideal case for examining whether this commitment is reflected in minor changes in vocal pitch that are indicative of legislators' emotional intensity. At the same time, our research also underscores, and extends our understanding of, the importance of descriptive representation in legislatures. Though male MCs can and do represent women, we posit that female legislators are able to speak about women in a way that male lawmakers generally do not.

In the sections that follow we first make the case for studying non-verbal aspects of political speech generally, and legislators' speech in particular. In doing so, we introduce vocal pitch as a measure of underlying emotional intensity. Focusing on women's representation as a crucial test case, we posit that female lawmakers' speech on behalf of women will be more intense, on average, than both men's speech on women and also women's speech on other issues. To assess these claims, we draw on text and audio from all 74,158 floor speeches that are at least 50 words in length given between 2009 and 2014 in the U.S. House. We use the text to determine whether a representative is talking about women and the audio to capture the emotional intensity of the speech—as measured by subtle changes in the lawmaker's vocal pitch relative to her baseline. As compared to other topics, we find that female MCs are especially intense when talking about women.

Having shown that female MCs speak with greater emotional intensity when referencing women, we then offer two sets of supplementary analyses. We first examine whether increased vocal pitch is consistent with legislators' issue commitments. To do so, we begin by demonstrating that the Congresswomen who are most emotionally intense when talking about women also have voting records that are rated more favorably by women's interest groups. We then confirm that the patterns observed in female MCs' speech on women hold more generally by showing that Democratic and Republican MCs speak with heightened pitch on issues traditionally owned by their respective parties.

In our second set of extensions, we broaden our work further to provide a preliminary assessment of lawmakers' responses to the emotional intensity of floor speeches—in this case examining whether, and in what ways, male MCs react to female legislators' speech through their own speech and voting behavior. Our preliminary results suggest that as the amount and intensity of women's speech increases, Congressmen respond by talking more (and more intensely) about women. Despite concerns about backlash effects, we find that greater numbers of women's speeches delivered with heightened emotional intensity are positively associated with male MCs voting with women. Taken together, our central finding and extensions demonstrate that studying the non-verbal aspects of political speech offers new insights into important political phenomena. We thus conclude by highlighting some avenues of future research related to this new method and data source.

The Non-Verbal Content of Legislative Speech

Existing scholarship examines many forms of Congressional behavior in order to draw inferences about legislators' ideologies (Poole and Rosenthal, 1985; Clinton, Jackman and Rivers, 2004; Poole and Rosenthal, 2001) and issue attention (Burden, 2007; Jones, Larsen-Price and Wilkerson, 2009; Sulkin, 2005; Woon, 2009). Although these studies provide significant insights into lawmakers' behaviors, they are limited in important ways. Roll call voting, for example, is largely constrained by party (Snyder and Groseclose, 2000). Bill sponsorship is not only time consuming, but also influenced by factors not easily controlled by legislators, such as staff size, seniority, and committee assignments (Schiller, 1995). As a result, it is difficult to determine the issues about which MCs feel more intensely, versus issue activities that are the result of party influence, constituency pressures, or institutional barriers.

We argue that legislative speech can be leveraged to gain a deeper understanding of MCs' emotional intensity around a given issue. Choosing to speak on the House floor is traditionally seen as position-taking (Mayhew, 1974), and the verbal content of floor speeches has been used to estimate legislators' ideologies (Diermeier et al., 2012). Yet, floor speeches offer more than just ideological positions. In particular, the non-verbal content of a legislator's speech—specifically, her vocal pitch—captures her emotional engagement with the issue at hand.

Vocal Pitch as a Measure of Emotional Intensity

Though understudied within legislatures, the non-verbal elements of speech have clear political ramifications. A growing body of work demonstrates that vocal pitch affects evaluations of candidates (Anderson and Klofstad, 2012; Anderson et al., 2014; Klofstad, Anderson and Peters, 2012; Klofstad, Anderson and Nowicki, 2015; Klofstad, 2016). This research shows both that differences in baseline vocal pitch can influence candidates' political prospects, and also that these effects are deeply gendered. Experimental studies, for example, suggest that citizens make inferences about competence and trustworthiness based on vocal characteristics (Anderson et al., 2014), and prefer female leaders with lower pitched voices (Klofstad, Anderson and Peters, 2012).

Despite the interest in political speech broadly, and newer work on the non-verbal elements of speech in particular, political science research has overlooked a central feature of speech: subtle variations within an individual's vocal pitch. These small deviations convey information about a speaker's emotional state. When individuals become emotionally activated, a typical physiological response is a tightening of the vocal cords. This tightening, in turn, leads to a higher-than-average vocal pitch when speaking. Indeed, studies have "routinely shown that [pitch]-related measures...are influenced by affect-related arousal" (Owren and Bachorowski, 2007, 240), and "higher levels of arousal have been linked to higher-pitched vocal samples" (Mauss and Robinson, 2009, 222).[1]

Although novel within political science research, the link between higher vocal pitch and emotional arousal is well-established in the psychology literature. Indeed, on pages S4–S16 of our Supplemental Information we provide an extended discussion of this link between vocal pitch and emotional intensity, including validation exercises.[2] These include studies that generate emotional intensity via acting prompts and those that induce emotional states via the Velten procedure. Here, we note that Bachorowski and Owren (1995) induced specific emotional states within respondents by asking them to complete a 210-trial word identification task on a computer. After each block of 10 words, the respondents received either positive ("Good Job") or negative ("Try Harder") feedback. Subjects were then asked to answer a battery of questions about their emotional state and read a block of text aloud. The authors showed that vocal pitch was higher when individuals reported higher levels of emotional intensity, leading them to conclude that pitch can be used to assess respondents' levels of emotional arousal.

These shifts in vocal pitch are subtle and difficult for the speaker to control. This physiological response, like many automatic responses, is thought to occur largely below conscious awareness. In this way, minor changes in vocal pitch serve as an "inherently honest indicator" of a speaker's "internal state" (Ekman et al., 1991, 133-134). This latter argument is supported by Zuckerman and Driver (1985), who argue that non-verbal behaviors reveal (or "leak") information that speakers are trying to hide. "Tone of voice," in particular, has been identified as an especially telling indicator. Indeed, "several studies have shown that...the tone of a person's voice leaks information that is not revealed by the verbal content or fa-

[1] It is important to note that the heightened emotional arousal indicated by increased vocal pitch does not convey complete information about a person's emotional state. Emotions can be thought of as having both valence (positive/negative or pleasant/unpleasant) and intensity (Russell, 1980). Vocal pitch is a measure of the latter. Thus, we would expect vocal pitch to increase under both a state of enthusiasm as well as a state of anger. Please refer to pages S5–S6 of the SI for a fuller discussion of the relationship between vocal pitch and emotional intensity.

[2] Though vocal pitch is a useful measure of emotional intensity, it is not the only measure that can be used to achieve this end. See pages S15–S16 in the SI for a discussion of the benefits and limitations of our approach.

cial expressions associated with the message" (Zuckerman and Driver, 1985, 129). For these reasons, verbal and non-verbal behavior can be thought of in terms of a "leakage hierarchy" with "verbal content" (i.e., the words spoken) located in the "controllable end of the continuum, whereas the body and tone of voice may be classified as less controllable and more leaky channels" (Zuckerman and Driver, 1985, 130). In fact, when individuals attempt to control their vocal pitch, they often sound "more tense and less pleasant or compelling than someone speaking sincerely," which is in turn associated with "increased vocal pitch" (Elkins et al., 2014, 505).[3] This difficulty in controlling vocal pitch makes it uniquely well-suited for studying the emotional states of strategic actors.

Emotional Intensity in Legislators' Speech

Finding a reliable indicator of emotional activation or intensity is especially important in the domain of legislative speech. Scholars have long recognized that much of a legislator's behavior is best understood as strategic actions used to meet her re-election or institutional goals. That is, the verbal content of speech is often seen as cheap talk (Austen-Smith, 1990). Indeed, "to the extent [that a] behavior furthers the actor's short-term self interests," Kraut (1978) argues that we should "discount an actor's behavior as a reflection of his or her true nature." For this reason, with legislative speech it is difficult to disentangle legislators' internal states from their strategic behavior.

[3]Emotional deception requires deliberate effort. Whether it is a friend feigning laughter or a politician displaying anger for strategic purposes, more work is required to convince others of false feelings. Not only do such efforts require more cognitive resources, but the constant thought of whether the fabricated performance is succeeding or failing increases the stress the individual feels. This often causes those involved in emotional deception to become overly concerned with their overt behaviors. For example, a friend trying to feign laughter might inadvertently laugh too much because she does not want to be exposed as a fraud. Indeed, "deliberate attempts by liars at controlling expressive behaviors, such as attempts to control thoughts and feelings, can be the seeds of their own destruction" (DePaulo et al., 2003, 78). This is not to say that vocal pitch is physically impossible to control for those with sufficient training in conveying emotions. For example, trained actors can successfully portray "strong" and "weak" emotions with convincing levels of "activation" and "intensity" (Laukka, Juslin and Bresin, 2005). However, especially in "deceptions which involve emotion" (Ekman et al., 1991, 133), speakers have a difficult time modulating their own vocal pitch to appear sincere. Thus, changes in vocal pitch are not only occurring largely below conscious awareness, but are also hard to fake.

Although lawmakers have ulterior motives when speaking in the legislature, some aspects of their speech may be outside their conscious control. Since "one should believe most in those aspects of a person's performance that the person is least able to deliberately and consciously control" (Kraut, 1978, 381), subconscious aspects of speech should serve as more meaningful signals of legislators' emotional states. With respect to legislative speech, features like "verbal content, speech rate and fluency, most body movements, and the large easy-to-see facial expressions, are all more susceptible to deliberate control" (Ekman et al., 1991). Speech topic, choice of words, and the length or extent of remarks each have a high degree of "controllability," and should thus be driven largely by legislators' strategic concerns. Vocal pitch, on the other hand, typically lies beyond the control of the individual (Ekman et al., 1991, 134). Since changes in pitch are less "controllable," they are a more honest indicator of a lawmaker's emotional intensity on a given issue.

This argument about the difficulty of controlling non-verbal aspects of speech has not been entirely lost on political scientists. Citing Goffman (1959), Fenno (1977) recognizes the importance of non-verbal expressions for evaluating the sincerity of legislators' behaviors. He says:

> Goffman is particularly interested in the second kind of expression - "the more theatrical and contextual kind" - because he believes that the performer is more likely to be judged by others according to the non-verbal than the verbal elements of his presentation of self. Those who must do the judging, Goffman says, will think that the verbal expressions are more controllable and manipulable by the performer; and they will, therefore, read his non-verbal "signs" as a check on the reliability of his verbal "signs" (898).

When MCs speak, they do so with a combination of controllable and manipulable elements, and relatively uncontrolled and sincere elements. The less easily controlled an element, the more likely that it measures the emotional disposition the speaker has toward the issues she is advancing. There is significant evidence that changes in pitch can arise from affective arousal, and that these variations in vocal pitch are associated with other noticeable emotional displays. Since such changes in vocal pitch are difficult to purposefully manipulate, discussing a topic with higher-than-average vocal pitch signals one's emotional intensity about that issue. We turn now to outlining a test case for our claims about emotional intensity: women's and men's legislative speech on women

Emotional Intensity and Women's Representation

The well-established link between women's numeric and policy representation makes Congressional speech on women an ideal test case for examining legislators' emotional intensity across policy arenas. Of course, men can (and do) act on behalf of women. Congresswomen also have a range of issue priorities, and working to represent women is not a primary concern for every female MC. Yet, scholars have pointed to a unique link between female lawmakers and female constituents, with women being more active on issues that are related to women, both within and beyond their districts (Carroll, 2002). This behavior has been attributed in part to women's shared lived experiences. Reingold (1992), for example, finds that female state legislators are "more likely to express some sort of commitment to representing women and/or women's concerns," arguing that "because of their gender, they felt uniquely qualified to handle the concerns of their female constituents" (531). As compared to other topics, we thus expect that in the aggregate female lawmakers are not only more likely to talk about women, but that they are especially emotionally engaged when doing so.

Existing work suggests that Congresswomen do, in fact, use floor speeches to draw attention to issues related to women. Hall (1998) notes that female MCs were more active on the House floor during the Job Training Partnership Act of 1982 and on the Older Americans Act, both of which were supported by the Congressional Caucus for Women's Issues. Pearson and Dancey (2011a, 2011b) show that female legislators are not only more likely to speak on the House floor than their male colleagues, but also to reference women in those speeches.

Osborn and Mendez (2010) likewise find that female senators speak more about health and family issues as compared to male senators. Shogan (2001) demonstrates that 11 percent of the statements made by female MCs mentioned the specific concerns of women, indicating that "female representatives often utilize the 'talking and deliberating' activity associated with descriptive representation to promote women's issues, interests, and concerns" (140).

Beyond the content of their speech, male and female legislators also differ in their rhetorical style, with women being especially likely to emphasize social bonds and personal experiences. Kathlene (1995) shows that female legislators are more likely than their male counterparts to emphasize the societal link to crime, leading them to speak more about long-term preventative strategies. This "connected" world view is also advanced by women in small group discussions (Karpowitz and Mendelberg, 2014) and other legislative debates (e.g., Levy, Tien and Aved, 2001). Based on her analysis of floor debates on five bills in the 104th Congress, Walsh (2002) suggests that women tend to expand the frame of discussion to not only mention women, but also to relate issues to their personal experiences. Swers (2002) makes similar claims. These differences in rhetorical style may also manifest in some aspects of nonverbal expression. Women, for example, use more smiling, nodding and gazing behavior. They also use greater facial and gestural expressiveness and smaller interpersonal distances (Hall, Carter and Horgan, 2000).

Female and male lawmakers' speech thus differs in both content and style. These differences should be especially pronounced in legislative speech referencing women. This is to be expected, given that when talking about women female MCs can speak "with a voice carrying the authority of experience" (Mansbridge, 1999, 644). Though previously unexamined, we posit that the effect of experience extends beyond content and style to influence Congresswomen's emotional intensity when referencing women. This suggests our central hypothesis: *on average, female MCs speak with elevated vocal pitch when talking about women* as compared both to women's average vocal pitch when discussing other topics and also men's vocal pitch when referencing women.

Data and Measurement

Testing our central hypothesis requires data on male and female legislators' vocal pitch when speaking about women as compared to other issue areas. To measure legislators' emotional intensity when speaking on a given topic, we turn to data from *HouseLive*.[4] *HouseLive* is an online service from the Office of the Clerk that provides live and archived video of proceedings in the U.S. House dating back to 2009. We focus our analyses on the audio and closed-captioning text information embedded in these videos. In total, we collected 6,432 hours of audio from 863 U.S. House debates beginning on January 6, 2009 and ending on August 4, 2014, representing the totality of debate occurring on the U.S. House floor over those five-and-a-half years.

Having collected all floor speeches given in this time period, we split each audio file into individual speeches using the timestamps found in the closed-captioning information. Focusing on speeches that have at least 50 words yielded audio and text for 74,158 speeches.[5] As we explain below, we use the audio data to extract the vocal pitch of each speech and the closed-captioning text to identify speech topic.

Importantly, in addition to contributing to Congressional scholarship, our work also provides an impressive corpus of "real-world" audio data. Past studies of emotions and vocal pitch have typically relied on either a small number of speakers induced into a particular emotional state, or trained actors asked to portray emotions (though without explicit instructions to vary their vocal pitch) (Scherer, 2013).[6] While Schuller et al. (2011) recognizes the importance of actor portrayals to the study of emotion and human speech, they also argue that "obtaining more realistic data will still be the most important issue in the foreseeable future" (1080). In line with this directive, our data encompass a vast number of utterances by hundreds of speakers conveying emotional content in a natural (to them) setting. Our

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[4] `http://houselive.gov`

[5] Speeches with under 50 words were typically procedural interjections or interruptions.

[6] Please see page S6 in the SI for a discussion of how deliberate portrayals of emotional intensity compare to exogenous manipulations of emotional states.

real-world application of vocal pitch as a marker for emotional content thus also contributes to the psychology literature on emotional intensity.

Measuring Emotional Intensity via Vocal Pitch

From our raw audio data, we compute changes in speakers' vocal pitch as our measure of emotional intensity. We first calculate speakers' baseline levels of vocal pitch, then measure variations in vocal pitch across speeches. Generally speaking, "voice pitch is the perceived 'highness' or 'lowness' of a voice and is influenced by the fundamental frequency" (Klofstad, 2016, 2). Following Titze (2000), the fundamental frequency (F_0) can be defined using the following equation:

$$F_0 = \frac{1}{2L}\sqrt{\frac{\sigma}{\rho}} \tag{1}$$

where L is the vocal fold length, σ is the longitudinal stress on the vocal folds, and ρ is the vocal fold tissue density. Individual variations in vocal fold length (L) and density (ρ) are largely determined by genetics (e.g. Przybyla, Horii and Crawford, 1992; Debruyne et al., 2002).[7] Conversely, variations in longitudinal stress (σ) are specific to the speaker and speech. Puts, Gaulin and Verdolini (2006, 285) demonstrate that "[e]motional activation raises F_0 by increasing tension on the vocal fold mucosa (σ, in Eq. (1)), mainly via contraction of the circothyroid muscles and consequent lengthening of the vocal folds."[8]

To measure pitch, we extract the mean fundamental frequency (F_0) – that is, the average vocal pitch – from each floor speech using *Praat*.[9] This commonly used speech analysis software estimates the fundamental frequency by dividing the autocorrelation of a windowed signal by the autocorrelation of the window itself.[10] Given that the pitch window can in-

[7] Additional details regarding our data can be found on pages S3–S4 in the Supplemental Information.

[8] Of course, other factors affect mean utterance pitch, including whether an utterance is a question, utterance duration, etc. However, as we show in our analyses, we find that mean vocal pitch appears to be a reliable indicator of emotional intensity even after controlling for many of these factors.

[9] http://www.fon.hum.uva.nl/praat/

[10] *Praat* implements a variation of the Boersma (1993) algorithm. The software can be downloaded at: http://www.fon.hum.uva.nl/praat/. To use this software, one has to set five parameters: the pitch floor,

fluence the vocal pitch estimate, on pages S22–S30 in the Supplemental Information we re-estimate all of our models using different *Praat* settings. The results remain essentially unchanged, regardless of the pitch window used.

In order to control for inter- and intra-speaker variation, we scale vocal pitch to standard deviations above or below the speaker's baseline. Author (2017) argues that this should be done for two reasons. First, in this project we are not interested in whether a lawmaker generally speaks at a higher vocal pitch. Rather, we are concerned with whether a legislator's vocal pitch changes from its baseline level when speaking about women. Standardizing vocal pitch not only helps capture whether a speaker is higher or lower than her average, but also gives the relative magnitude of the change. Second, although studies find few gender differences in the vocal characteristics used to convey emotions—such as laryngeal tension, lip rounding, pitch level and range, loudness, clarity, and rate (Bezooyen, 1984; Brody, 2009; Davitz, 1964)–because women's vocal cords tend to be smaller and shorter, they do typically speak at a higher baseline vocal pitch than men. By standardizing vocal pitch using each speaker's baseline (or mean) vocal pitch, we account for this inherent sex difference.

Identifying Speech Topic

Individual-level variation in vocal pitch provides a measure of emotional intensity. We expect that levels of emotional activation vary by speech topic. We use the closed-captioning text data from *HouseLive* to determine whether a MC addressed women in a given speech. We opt for closed-captioned transcripts because they more accurately report what is said on the House floor than the *Congressional Record*. Legislators can change the *Congressional Record* after the fact, and often read in text that was not spoken on the House floor (e.g., asking that a letter from a constituent be added to the *Congressional Record* instead of reading it

pitch ceiling, window length, window shape, and voicing threshold. For the pitch floor and ceiling, we used *Praat* suggested settings, meaning for men, we set the pitch floor to 75Hz and the ceiling to 300Hz. For women, we used a pitch range of 100 to 500Hz. For both the window shape and voicing threshold we used the default settings.

aloud). Since it is directly transcribed, closed-captioning information does not suffer from this limitation.[11]

To establish whether the speaker addressed women we create a binary variable indicating whether the speech used any of the Pearson and Dancey (2011*b*) dictionary terms related to women. These include "woman," "women," "woman's," "women's," "girl," "girl's," "girls," "girls'," "female," "female's," "females," "females'," "servicewoman," "servicewoman's," "servicewomen" and "servicewomen's." If a speech contains any of these terms it is coded as a 1, otherwise 0. Given that this is a coarse measure of whether a speech addresses women, we also estimate all models using two alternative operationalizations of the dependent variable. The first considers the proportion of words in the speech drawn from these dictionary terms. The second identifies speech about women using a Structural Topic Model (STM) (Roberts et al., 2013; Roberts, Stewart and Tingley, 2014; Roberts et al., 2014). Irrespective of the way we measure the degree to which a speech addressed women, the results are identical to those outlined below. The models using alternative approaches are reported on pages S30–S36 in the Supplemental Information.

Modeling Strategy

Our key predictor of interest is speaker sex, which we obtain from *GovTrack*.[12] We view each speech as a unique opportunity to address women. We thus use the legislative speech (rather than the legislator) as our unit of analysis. Aggregating to the legislator level would obfuscate the important within-individual variation that takes place from speech to speech.

[11] As closed-captions are produced in real-time, typographical errors may be a concern. In email correspondence, the company that performs the closed-captioning service for the House of Representatives asserts that their transcribers are generally 95 percent accurate–i.e., 95% of words transcribed are the words actually spoken on the House floor. This assessment is based on yearly evaluations, in which the company randomly selects a certain number of transcripts from each of their transcribers and determines the degree to which those transcripts capture the floor debate for that day. For this study, we transcribed 100 randomly selected speeches. When we compared our transcribing to the closed-captioning information, the closed-captions essentially mirrored the transcripts (regardless of the similarity measure used). Based on these results and our communication with the closed-captioning company, we are confident that the closed-captioning found on *HouseLive* is an accurate reflection of what is said in the U.S. House.

[12] `https://www.govtrack.us`

For example, a single emotionally activated speech could artificially inflate a MC's mean vocal pitch – giving the impression that she is an emotive legislator when in reality she generally delivers subdued speeches (with one extreme exception). At the same time, because speeches given by the same MC will likely share commonalities, we estimate multilevel linear and logistic regressions with random intercepts for each legislator. This modeling approach also helps to account for other unobserved differences between legislators that could influence the parameter estimates.

We also control for other factors that may bias the results if omitted. Members who are institutionally disadvantaged are forced to take to the floor more often in an attempt to influence legislation (Maltzman and Sigelman, 1996), as they have fewer other tools at their disposal. We therefore include measures of speaker race and seniority from *GovTrack*, and use data from Stewart and Woon (2016)[13] to determine whether the speaker was a committee chair. We also incorporate data on partisanship and ideology from *Voteview*,[14] both of which have been shown to influence floor speeches (Morris, 2001; Harris, 2005). For similar reasons, we include dummy variables for whether the speech was less than one minute and whether it was delivered during an election year, both of which have been shown to influence speaking behavior (Maltzman and Sigelman, 1996). We also incorporate a control for the speech duration, since spikes in vocal pitch will have a greater effect on mean vocal pitch when a speech is shorter. Finally, on pages S49–S86 of the Supplemental Information, we further replicate these results with a number of different model specifications.

Results: Legislators' Vocal Pitch when Referencing Women

To begin, if the link between numeric and policy representation leads female MCs to speak with more emotional intensity about women, then we would likewise expect female MCs to speak more frequently about women than their male colleagues. We thus first establish that

[13] http://web.mit.edu/17.251/www/data_page.html

[14] http://voteview.com

female lawmakers are on average more likely to talk about women in their floor speeches. In total, Congresswomen include at least one of the Pearson and Dancey (2011*b*) dictionary terms in 2,403 of their 13,484 total speeches (17.82%). Male MCs, in contrast, use a dictionary term in 5,507 of 60,667 speeches (9.08%). We further verify this expectation in Models 1.1 (Table 1, Model 1) and 1.2 (Table 1, Model 2). Here, the dependent variable is whether a given floor speech used a word from Pearson and Dancey (2011*b*)'s "women" dictionary. The predictor of interest is `Female`, which equals 1 if the MC is a woman and 0 otherwise. Like previous studies, our findings indicate that female legislators are, in fact, more likely to talk about women in their speeches. Based on our results from Model 1.1, women in Congress are 2.13 times more likely to reference women as compared to male MCs (predicted probabilities of 0.17 for women and 0.08 for men). This holds even after accounting for party identification, ideology, institutional position, seniority, race, and whether it was an election year (see Model 1.2).

Though this is an important finding in and of itself, it is difficult to assess the degree to which female MCs are emotionally invested in speaking about women using only the text and topics of their speeches. In Table 2 we present the mean and standard deviation of men's and women's vocal pitch by party. Here, higher values mean that the MC is speaking with greater emotional intensity. Comparing the first and second columns shows female MCs speak at a significantly higher vocal pitch when using one of the Pearson and Dancey (2011*b*) terms (t = 4.14, df = 12917, $p \leq 0.001$). More specifically, both Democratic (t = 3.12, df = 8967, $p \leq .01$) and Republican women (t = 2.81, df = 3948, $p \leq .01$) have markedly higher vocal pitch when they reference women as compared to when they do not.[15] The same cannot be said for male MCs, whose vocal pitch remains essentially unchanged when

[15] When referencing women, Republican Congresswomen have an average vocal pitch of 207.02Hz. Democratic Congresswomen have an average vocal pitch of 205.68Hz. There is no significant difference between the vocal pitch of Democratic and Republican women when speaking about women ($t = -1.02$, df = 2257, $p \leq 0.31$). This suggests that female MCs tend to generally speak at a higher vocal pitch when using at least one of the Pearson and Dancey (2011*b*) terms and that this difference cannot be easily attributed to party identification.

Table 1: Female MCs More Likely to Talk About Women, with Greater Intensity

	Dependent variable:			
	"Women" Mentioned		Standardized Vocal Pitch	
	(1)	(2)	(3)	(4)
Fixed Effects				
Constant	-2.427^{***}	-2.218^{***}	-0.002	0.151^{***}
	(0.035)	(0.183)	(0.004)	(0.024)
Female	0.866^{***}	0.790^{***}	-0.017	-0.032^{***}
	(0.078)	(0.081)	(0.011)	(0.011)
Democrat		-0.227		-0.039
		(0.221)		(0.029)
DW-Nominate		-0.396^{*}		-0.033
		(0.205)		(0.026)
Seniority		-0.008^{**}		0.0003
		(0.003)		(0.0004)
Committee Chair		0.063		-0.048^{***}
		(0.063)		(0.014)
White		-0.059		0.013
		(0.115)		(0.014)
One Minute		-0.948^{***}		-0.379^{***}
		(0.039)		(0.009)
Duration		0.084^{***}		0.002^{**}
		(0.003)		(0.001)
Election Year		0.142^{***}		-0.088^{***}
		(0.026)		(0.008)
"Women" Mentioned			0.020	-0.054^{***}
			(0.014)	(0.014)
Female × "Women" Mentioned			0.090^{***}	0.112^{***}
			(0.027)	(0.027)
Random Effects				
MC	0.399	0.386	0.000	0.000
	(0.044)	(0.053)	(0.000)	(0.000)
N_1	74,151	74,151	71,198	71,198
N_2	619	619	613	613
Log Likelihood	$-23{,}909.700$	$-22{,}786.800$	$-100{,}720.100$	$-99{,}645.100$
AIC	47,825.410	45,595.610	201,452.100	199,318.200

Note: In Models 1 and 2, the dependent variable equals 1 if the speech included any of the Pearson and Dancey (2011*b*) women's dictionary terms, 0 otherwise. These models report the results from a multilevel logistic regression. In Models 3 and 4, the dependent variable is the speaker's vocal pitch in standard deviations above or below the speaker's baseline. These models report the results from a multilevel linear regression. All models also include a randomly varying intercept for each member of Congress. Levels of significance are reported as follows: *p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01. Standard errors are reported in parentheses.

referencing women ($t = 0.02$, df $= 58281$, $p \leq 0.99$). Indeed, neither Democratic ($t = -0.43$, df $= 25868$, $p \leq 0.67$) nor Republican men ($t = 0.33$, df $= 32411$, $p \leq 0.75$) significantly change their vocal pitch when talking about women.[16]

Table 2: Average Vocal Pitch and Standard Deviation for Male and Female MCs by Party

	"Women" Mentioned		"Women" Not Mentioned	
	Pitch Mean	Pitch SD	Pitch Mean	Pitch SD
Male				
Republican	151.11	24.28	150.95	24.51
Democrat	151.94	24.29	152.17	25.65
All	151.50	24.28	151.49	25.03
Female				
Republican	207.02	30.27	203.11	30.52
Democrat	205.68	25.64	203.35	28.25
All	206.01	26.87	203.27	28.99

Note: Measurements of vocal pitch are in Hertz (Hz). In the first two columns, we restricted our data to speeches which used at least one of the terms outlined by Pearson and Dancey (2011*b*). In the last two columns, we restricted our data to speeches which did not use any of these terms. Rows correspond to indicated groups. For example, the average vocal pitch for all speeches delivered by Republican men mentioning women was 151.11Hz. Averages for each column can be found in the "All" rows.

Moving beyond descriptive statistics, in Models 1.3 and 1.4 we predict speaker's vocal pitch, as measured in standard deviations above or below his or her baseline. Here, positive values mean that the MC is speaking with more emotional intensity than we would otherwise expect, whereas the inverse is true for negative values. We test whether female MCs demonstrate greater emotional intensity when talking about women than other topics (our central hypothesis) by interacting `Female` with a dummy variable indicating whether a given speech used any of Pearson and Dancey (2011*b*)'s dictionary terms about women (`''Women'' Mentioned`).

[16]Additional details and other descriptive statistics can be found in Section S3 in the Supplemental Information. For a similar table comparing the mean and standard deviation of men's and women's standardized vocal pitch by party please refer to Table S3.

The significant interaction effect found in Table 1, Model 3 (Model 1.3) shows that female legislators speak with a higher vocal pitch when referencing women than when talking about other topics. When female legislators use any of the Pearson and Dancey (2011*b*) dictionary terms, their vocal pitch is 0.09 standard deviations higher than their baseline. This is nearly five times greater than male MCs, whose vocal pitch only increases 0.02 standard deviations when referencing women. At the same time, the raw magnitude is slight enough that this change in vocal pitch is likely beyond the control of the speaker. This finding holds even when traditional predictors of legislative behavior are included in Model 1.4, which suggests that our measure of emotional intensity is capturing information that scholars would otherwise miss. Related work by Dietrich, O'Brien and Yao (2019) suggests that similar results hold when analyzing word-level vocal inflections.[17]

Our results shed new light on the relationship between women's numeric and policy representation. Moving beyond studies that focus only on the verbal content of legislative speech, we demonstrate that women lawmakers are not only more likely to discuss women, but are also more emotionally engaged on average when doing so. Of course, not all female MCs express the same level of emotional intensity when speaking about women, and some male MCs are especially emotionally engaged on this topic. There are also likely other individual-level characteristics not captured by our covariates that affect legislators' propensity to speak with intensity about women. Yet, the fact remains that even when controlling for a myriad of other factors, female MCs are more likely to speak with above-average vocal pitch when referencing women than when referencing other issues and as compared to their male counterparts. Given the well-established relationship between women's numeric and policy representation, moreover, our findings support our argument that small deviations

[17]Plots of these predicted probabilities with confidence intervals can be found in Figure S9 on page S45 in the Supplemental Information. We also estimated separate models for Democrats and Republicans on pages S41–S49. Tables S17 and S18 show the results for Models 1.1 and 1.2 hold for both Democrats and Republicans. However, for Models 1.3 and 1.4 the interaction between `Female` and `''Women'' Mentioned` is only statistically significant for Democrats, even though the interaction is in the predicted direction for Republicans. Of course, this finding could be influenced by the comparatively smaller number of women in the Republican caucus, which makes it harder to detect an effect.

from baseline vocal pitch represent a novel measure of legislators' emotional intensity more broadly.

Emotional Intensity and Legislators' Issue Commitments

Thus far we have introduced a novel measure of legislators' emotional intensity and shown that female MCs, on average, are especially intense when speaking about women. We now turn to two additional analyses that explore whether increased vocal pitch is consistent with legislators' broader issue commitments. First, we examine whether female lawmakers' vocal pitch on women is associated with their voting behavior on women's issues. Second, we assess whether our findings hold for Democratic and Republican legislators speaking on issues owned by their respective parties.

Vocal Pitch and Interest Group Ratings

If increases in vocal pitch reflect legislators' emotional intensity about a topic, then vocal pitch should be associated with other types of legislative activity related to the issue area. To this end, we examine whether female MCs' emotional intensity when speaking about women is associated with differences in voting behavior on women's issues. To do so, we use legislative scorecards from 24 prominent women's interest groups, as reported by *Project Vote Smart*. These scorecards are used by interest groups to inform their members about which lawmakers are more or less likely to cast votes that are consistent with the organization's mission.[18] We collapse these scores into the average vote score for each legislator across all 24 groups for all available years of data, and use this information to examine voting patterns among female lawmakers.

[18] Legislative scorecards typically consist of a series of legislative votes that are relevant to the interest group. If legislators voted in the group's preferred direction, then they receive a 1 (or +), otherwise they receive a 0 (or −). The percent of the time legislators vote in the preferred direction is their "score" which is normally standardized from 0 to 100, with 0 being the legislator never voted in the preferred direction and a 100 being the legislator always voted in the preferred direction. More details can be found on the *Project Vote Smart* website (`https://votesmart.org`). Table S4 in the Supplemental Information (see page S21) provides the full list of groups used for the "Vote Smart" column in Table 3.

Table 3: Emotionally Intense Congresswomen are Rated More Highly by Women's Interest Groups

(a) *Most* Activated

	"Women" Ment.	"Women" Not Ment.	Pitch Diff.	Vote Smart
Name				
Sánchez (D-CA)	239.58	208.48	31.10	67.62
Brown (D-FL)	236.62	212.66	23.95	68.14
Davis (D-CA)	200.52	180.19	20.33	68.55
Halvorson (D-IL)	255.86	236.64	19.22	52.40
Herseth (D-SD)	213.40	194.86	18.54	65.72
Emerson (R-MO)	205.15	188.06	17.09	31.46
Wasserman (D-FL)	203.06	186.04	17.01	76.17
Lofgren (D-CA)	207.03	194.45	12.59	70.26
Moore (D-WI)	196.51	183.96	12.55	73.30
Speier (D-CA)	215.41	204.95	10.45	69.46
Lujan (D-NM)	224.21	214.10	10.11	49.53
Brownley (D-CA)	245.15	235.33	9.82	54.47
Titus (D-NV)	220.17	210.37	9.80	53.83
Eshoo (D-CA)	212.99	203.45	9.55	71.89
Fudge (D-OH)	194.69	186.40	8.30	59.30
Jenkins (R-KS)	198.39	190.22	8.17	29.24
Hochul (D-NY)	208.00	199.84	8.16	56.25
Baldwin (D-WI)	238.84	230.73	8.11	63.63
McCarthy (D-NY)	210.95	203.55	7.40	64.47
Hartzler (R-MO)	228.41	221.30	7.11	28.28
Dahlkemper (D-PA)	205.24	198.54	6.70	55.60
Roybal-Allard (D-CA)	212.54	205.85	6.69	70.37
Frankel (D-FL)	205.51	198.89	6.62	49.87
Woolsey (D-CA)	218.12	211.95	6.17	74.97
Lee (D-CA)	199.07	193.04	6.03	70.34
Groups				
All	215.82	203.75	12.06	59.81
Democrats	216.52	204.29	12.24	63.92
Republicans	210.65	199.86	10.79	29.66

(b) *Least* Activated

	"Women" Ment.	"Women" Not Ment.	Pitch Diff.	Vote Smart
Name				
Kilpatrick (D-MI)	189.49	225.66	-36.17	64.55
Herrera (R-WA)	200.15	221.99	-21.85	38.82
Kirkpatrick (D-AZ)	223.74	234.43	-10.69	51.47
DelBene (D-WA)	175.74	186.23	-10.49	50.53
Myrick (R-NC)	208.27	218.32	-10.04	27.43
Negrete (D-CA)	192.38	201.92	-9.54	48.20
McCollum (D-MN)	220.90	228.93	-8.03	70.32
Blackburn (R-TN)	250.37	257.36	-6.99	25.42
Meng (D-NY)	196.50	203.45	-6.95	46.93
Bachmann (R-MN)	213.18	219.18	-6.01	26.79
Bustos (D-IL)	192.24	197.66	-5.42	56.13
Beatty (D-OH)	180.63	185.58	-4.94	51.13
Hahn (D-CA)	212.97	217.84	-4.87	52.07
Kuster (D-NH)	226.97	231.75	-4.79	47.80
Harman (D-CA)	189.46	193.65	-4.19	65.59
Hanabusa (D-HI)	210.85	214.89	-4.03	52.81
Noem (R-SD)	219.65	223.61	-3.96	31.79
Shea-Porter (D-NH)	229.16	233.01	-3.85	64.52
Kaptur (D-OH)	197.61	201.35	-3.73	66.73
Berkley (D-NV)	184.68	188.22	-3.54	66.45
Granger (R-TX)	154.41	157.89	-3.48	25.04
Duckworth (D-IL)	200.44	203.81	-3.36	53.53
Kelly (D-IL)	141.00	144.26	-3.26	33.25
Waters (D-CA)	223.22	226.48	-3.26	70.90
Kosmas (D-FL)	185.92	189.12	-3.20	45.90
Groups				
All	200.80	208.26	-7.47	49.36
Democrats	198.63	205.70	-7.07	55.73
Republicans	207.67	216.39	-8.72	29.22

Note: Measurements of vocal pitch are in Hertz (Hz). In the first column, we restricted our data to speeches which used at least one of the terms outlined by Pearson and Dancey (2011*b*). In the second column, we restricted our data to speeches which did not use any of these terms. The "Pitch Difference" column (abbreviated "Pitch Diff.") is the difference between these two columns. The 25 *most* (see Panel A) and *least* activated (see Panel B) female MCs had the highest and lowest "Pitch Difference," respectively. The average vote score from 24 prominent women's interest groups (as reported by *Project Vote Smart*) is found in the column labeled "Vote Smart." A full list of the groups we used can be found in Table S4 in the SI. Higher values imply the MC cast more votes that are consistent with the mission of these groups. Column averages for Democratic and Republican women can be found in the "Groups" section.

Though on average Congresswomen speak with higher-than-baseline pitch when referencing women, Table 3 demonstrates that there is substantial variation in female MCs' emotional intensity when addressing this topic. Importantly, we find that the Congresswomen who speak with the greatest intensity about women receive significantly higher scores from women's interest groups than those who speak with the lowest intensity. In fact, there is a statistically significant difference between the average vote scores for the 25 most (Table 3a) and least (Table 3b) activated women ($t = 2.59$, df $= 48$, $p \leq .02$). This suggests that the female legislators who are especially emotionally intense when referencing women also have voting records that reflect their interest in representing women.

Of course, interest groups associated with women tend to skew Democratic, so our results are likely to be stronger for female Democratic MCs. As expected, when we conducted separate tests for each party, we found a statistically significant difference between the average vote scores for the most and least emotionally intense Democratic women ($t = 2.83$, df $= 39$, $p \leq 0.01$). These results did not hold for Republican women ($t = 0.14$, df $= 7$, $p > 0.05$), though we note that there are far fewer observations in this category. Moreover, although falling outside of the conventional bounds of statistical significance, the most intense Republican women are still rated higher than the least intense women. Our strong findings for Democratic women – and suggestive results for Republican MCs – together offer additional support for our claim that changes in vocal pitch can be used to capture legislators' emotional intensity around a given issue.

To further validate this claim, on pages S79–S81 in the SI we interact our vocal pitch measure with the number of women's issue bills introduced as defined by Volden, Wiseman and Wittmer (2016). We find that Congresswomen who introduce more women's bills also tend to speak with higher vocal pitch when referencing women than when speaking about other issues.We also replicate this analysis on pages S81–S84 in the SI with a second measure of legislative activity on behalf of women: the MC's average women's interest group rating. Here too we find that female lawmakers who tend to vote in the preferred direction of women's interest groups (as defined by *Project Vote Smart*) also speak with greater emotional intensity when talking about women as compared to their speech on other topics. These results are not only consistent with our broader argument, but also demonstrate that vocal pitch may yield additional insights when used in conjunction with more traditional measures of substantive representation.[19]

Vocal Pitch and Partisan Issue Ownership

Our work on female lawmakers suggests that we will observe heightened vocal pitch among MCs who have a broader commitment to the policy under discussion. As a further exploration of this claim, we turn now to an analysis of the speaking behavior of partisans in the U.S. House on issues that are traditionally "owned" by the Democratic and Republican Parties. If emotional intensity is associated with legislators' issue commitments, then we should observe Democrats in Congress speaking with heightened pitch on traditionally Democratic issues as compared to both Republican issues and also those that are owned by neither party. Likewise, we expect Republicans to express greater emotional intensity when speaking about topics that are especially important to their party. To assess this claim, we examine variations in vocal pitch above or below the speaker's baseline on issues that are more likely to be associated with Democrats and Republicans.

Using a 30-topic structural topic model (STM) to categorize the content of legislative speeches (see pages S30–S32 in the Supplemental Information for more information), we select a number of topic areas that correspond to widely-acknowledged partisan-owned issues.

[19]Heightened pitch may reflect not only an increased emotional commitment to representing women, but also MCs' greater confidence in working on and speaking about women's issue bills. Indeed, people who are deeply committed to an issue are both more likely to be emotionally intense when speaking about it and more likely to develop expertise on the topic. The aim of this paper is not to disentangle emotional activation from confidence. We do note, however, that our results for female legislators hold even when accounting for other measures of confidence, including the number of women's bills introduced by each MC. We also do not observe the same relationship among male lawmakers. Even those Congressmen who were most active on women's interest bills—and thus should feel most confident with respect to this issue area—did not exhibit more emotional intensity when talking about women. Thus, though emotional intensity is undoubtedly linked to confidence and expertise, it also offers information that would not be provided by more conventional measures of these phenomena.

For Democratic-owned issues, we identify nine topic categories that generally correspond to broader issues related to social welfare, land management/infrastructure, and civil rights. For Republican-owned issues, we identify nine topic categories that generally correspond to defense, immigration, and budget/tax policy.[20] Although it is beyond the scope of this paper to resolve debates about which issues are owned by the respective parties (e.g, Petrocik, 1996; Petrocik, Benoit and Hansen, 2003), these topics are widely recognized by the general public as Democratic and Republican issues (Goggin and Theodoridis, 2017).

As a validation of our identification of Democratic- and Republican-owned issues, we should find that legislators' speeches contain more language that falls under their party's owned issues. Indeed, we find that Republicans talk more about Republican-owned issues as compared to Democrats ($t = 30.51, df = 74135, p < 0.001$), and Democrats talk more about Democratic-owned issues than Republicans ($t = 18.43, df = 74047, p < 0.001$). This corresponds to Democrats using 9.02% more words – and Republicans using 17.21% more words – related to their respective party-owned issues. Although these differences may seem relatively small, the topics we extract from our STM capture less than 8% of the words in a given speech on average. This is because STMs – like other forms of Latent Dirichlet Allocation (LDA) topic modeling – view speeches as mixtures of several "topics," many of which are not issues but rather reflect different types of speaking styles (e.g., being more collegial or deferential). Words from a single issue are thus rare as compared to the entire corpus of words used in a speech.

Table 4 displays our results for changes in vocal pitch for Democratic- and Republican-owned issues. The positive and statistically significant interaction term in Models 4.1 and 4.2 indicates that Democrats speak with higher vocal pitch when speeches reference more Democratic-owned issues. Conversely, the statistically significant interaction term in Models

[20] The top five words in each topic category can be found in Table S15 in the Supplemental Information. This table can be found on page S38. We do not include the topic associated with women in the Democratic-owned issues because we use that topic as a dependent variable in Section S5.1 in the Supplemental Information. Please see Tables S10–S14 on pages S33–S37.

Table 4: Partisans Talk about Party Issues with Greater Intensity

(a) Democratic Issues

	Dependent variable: Standardized Vocal Pitch (1)	(2)
Fixed Effects		
Constant	0.022**	0.177***
	(0.009)	(0.025)
Democrat	−0.087***	−0.109***
	(0.014)	(0.031)
Democratic Issue	−0.090***	−0.138***
	(0.031)	(0.031)
DW - Nominate		−0.029
		(0.026)
Seniority		0.0004
		(0.0004)
Committee Chair		−0.046***
		(0.014)
Female		−0.019*
		(0.010)
White		0.013
		(0.014)
One Minute		−0.377***
		(0.009)
Duration		0.002
		(0.001)
Election Year		−0.088***
		(0.008)
Democrat × Democratic Issues	0.328***	0.288***
	(0.045)	(0.044)
Random Effects		
MC	0.000	0.000
	(0.000)	(0.000)
N_1	71,197	71,197
N_2	613	613
Log Likelihood	−100,699.200	−99,632.380
AIC	201,410.400	199,292.800

(b) Republican Issues

	Dependent variable: Standardized Vocal Pitch (3)	(4)
Fixed Effects		
Constant	0.017*	0.147***
	(0.009)	(0.019)
Republican	−0.087***	−0.048
	(0.013)	(0.031)
Republican Issue	−0.084**	−0.189***
	(0.035)	(0.035)
DW - Nominate		−0.026
		(0.026)
Seniority		0.0003
		(0.0004)
Committee Chair		−0.047***
		(0.014)
Female		−0.017*
		(0.010)
White		0.016
		(0.014)
One Minute		−0.377***
		(0.009)
Duration		0.002*
		(0.001)
Election Year		−0.088***
		(0.008)
Republican × Republican Issues	0.380***	0.355***
	(0.048)	(0.048)
Random Effects		
MC	0.000	0.000
	(0.000)	(0.000)
N_1	71,197	71,197
N_2	613	613
Log Likelihood	−100,686.500	−99,625.450
AIC	201,385.000	199,278.900

Note: The dependent variable is the speaker's vocal pitch in standard deviations above or below the speaker's baseline. In Panel A, we consider whether Democrats (`Democrat`) tend to raise their vocal pitch when speaking about Democratic-owned issues (`Democratic Issues`). In Panel B, we consider whether Republicans (`Republican`) tend to raise their vocal pitch when speaking about Republican-owned issues (`Republican Issues`). The issues themselves are derived from the Structural Topic Model (STM) outlined on pages S30–S32 in the Supplemental Information. All models are multilevel linear regressions and include randomly varying intercepts for each member of Congress. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

4.3 and 4.4 indicates that Republicans speak with a higher vocal pitch when speeches reference more Republican-owned issues. Moreover, the negative main effects for Democratic- and Republican-owned issues suggests that Democrats and Republicans speak at a significantly lower vocal pitch when referencing issues owned by the opposing party. On pages S20–S22 in the Supplemental Information, we further show that MCs who are closest to their party's median voting behavior (as measured by DW-NOMINATE scores) are more emotionally intense on their party's issues as compared to legislators who are further from the party median.[21]

Petrocik, Benoit and Hansen (2003) argue that partisans have more credibility when talking about their party's issues in part "because typical Democrats (or Republicans) believe in the concerns of their party" (602). This argument is consistent with our results, as Democrats and Republicans speak with more emotional intensity when discussing their party's core issues as compared to those owned by the opposition. Moreover, the slight changes we isolate are also consistent with vocal pitch being an indicator of a lawmaker's emotional disposition towards an issue. Policy topics that are central to a party's identity should elicit a stronger emotional reaction from party members, which is exactly what we observe in the rising vocal pitch of Democrats and Republicans in Congress when discussing issues owned by their parties.[22]

Heightened emotional intensity thus appears to correspond to policy commitments. Female MCs who speak at higher standard deviations above their baselines when referencing women also demonstrate their commitment to women through their voting behavior (as mea-

[21] A listing of which members are most and least activated when talking about party issues can be found in Table S5 in the Supplemental Information. This table can be found on page S23.

[22] This analysis also helps us rule out an alternative explanation for female legislators' heightened vocal pitch when discussing women: anxiety. Given that legislators speak with higher vocal pitch on issues owned by their party, and decreased pitch on issues owned by the opposing party, it is highly unlikely that pitch changes simply reflect lawmakers' greater anxiety when speaking about owned issues. Indeed, this would run counter to scholarship on issue ownership by Petrocik and others (Petrocik, 1996; Petrocik, Benoit and Hansen, 2003), which assumes that partisans advance party issues because they are thought to be better able to handle them. In Section S8.8 of the SI, we conduct an additional analysis in which we leverage an MC's first speech in a given Congress to further demonstrate that our measure of emotional intensity is not simply picking up general anxiety about speaking on the floor of Congress.

sured by interest group ratings). And, Democrats and Republicans speak on issues owned by their party with greater intensity than on other issues. Together, these supplementary analyses provide further evidence consistent with our claim that a legislator's vocal pitch signals her emotional intensity about the issue she is discussing.

Legislators' Responses to Heightened Vocal Pitch

Having established that vocal pitch can be used as a measure of legislators' emotional engagement with a given issue area, we conclude our empirical analyses with a preliminary assessment of the broader implications of this speech. In particular, we ask whether emotionally intense speech by women is associated with changes in other lawmakers' behavior. MCs' floor speeches can provide information to both their constituents and also to their fellow legislators. Even when lawmakers are not physically present on the floor, the rise of C-SPAN means that they are devoting more time to both giving and paying attention to floor speeches. As Kingdon (1989) notes, "it has become common for members or their staffs to listen to the debate on the set in the office, keeping one ear on the proceedings while attending to other kinds of work" (103).

Though it is impossible to say with certainty which MCs observe floor speeches, we expect that some lawmakers do hear (about) them, especially when delivered in large numbers and with emotional intensity. As a result, we believe that floor speeches have the potential to send meaningful signals to other legislators. Returning to our test case, we may be especially likely to observe effects with respect to Congresswomen's speech about women. Work on men and women in deliberative settings shows that male behavior responds to changes in women's presence and participation (Mendelberg, Karpowitz and Oliphant, 2014). Focusing on the judiciary, Boyd, Epstein and Martin (2010) find that male judges turn to their female colleagues when deciding cases directly related to women. We may see similar effects in Congress. When a large number of female legislators talk about women, they signal that the topic will impact women in their colleagues' districts. Since constituency pressures are a powerful force shaping speaking behavior (Maltzman and Sigelman, 1996), male legislators may subsequently take to the floor to discuss women as a means to address concerns that are salient to their female constituents.

The clarity of these signals should be influenced not just by the frequency with which female legislators speak, but also the intensity. Exposure to female legislators' emotionally intense speeches by and about women should activate other legislators' emotions, leading them to become more emotionally intense themselves. Moreover, whereas a single legislator speaking at a slightly higher vocal pitch may not send a very strong signal, several speeches delivered in such a way start to carry considerable weight (particularly when those speeches are delivered by women about women). That is, a large number of emotionally intense speeches delivered on the same day is not only likely to get the attention of male MCs, but is also likely to influence their behavior.[23] Although providing a direct causal test of this claim is beyond the scope of this paper, below we offer suggestive evidence consistent with male legislators responding to women's speeches.

Amount and Intensity of Men's Speech on Women

To examine men's response to female MCs' speech on women, we first extend our main analysis to consider men's willingness to address women in their floor speeches (see Table 5). In Models 5.1 and 5.2, the dependent variable is whether a given Congressman's floor speech contained one of Pearson and Dancey's (2011*b*) women's dictionary terms. Our primary independent variables are (1) the number of speeches delivered by women on a given legislative day that reference women (`Female Speeches`), and (2) the average vocal pitch of those speeches (`Female Pitch`). We are thus interested in the interaction between `Female Speeches` and `Female Pitch`. A positive and statistically significant interaction term would be consistent with male MCs becoming more likely to mention women when female MCs

[23] We also test whether a single emotionally intense speech can influence a subsequent male speaker using dyadic models. These results offer further support to the findings we present below. See pages S55–S65 in the Supplemental Information for more information.

deliver a large number of speeches about women at an increased vocal pitch.

We restrict our analysis to male MCs who delivered speeches on the same legislative day as female speeches about women for which we have vocal pitch data. This restriction allows us to focus on those male legislators who are most likely to have been influenced by Congresswomen's behavior.[24] We also include two additional controls for the types of issues being debated on a given legislative day. First, we want to isolate the impact of female MCs' speech from the general effects of women's heightened issue activity. To do so, we draw on Volden, Wiseman, and Wittmer's (2016) "women's issues" measure to include a variable counting the number of bills debated in their six "women's issues" categories.[25] This provides a general proxy for whether issues highly salient to women in Congress appeared on the day's agenda. Second, we are concerned that both male and female MCs may speak with greater emotional intensity when important issues are being debated. In these instances, we would expect the vocal pitch of male and female legislators to be heightened, leading to the impression that women's speech is influencing male behavior when in reality both groups are responding to the importance of the issue itself. To account for this possibility, we use *CQ Weekly*'s "Bills to Watch"[26] to create a count variable of the number of major bills debated on each legislative day.[27]

[24]Although we acknowledge that we cannot be sure that all male MCs who spoke on the same day were in the chamber for their female colleagues' speeches, we believe that this is the most appropriate modeling strategy. No data is available on which legislators are physically present during floor speeches, and including all male MCs who served during that Congress would introduce needless noise. Moreover, even if male legislators who spoke on the same day were not physically present during their female colleagues' speeches, they should be more attuned to the happenings on the floor via C-SPAN or other methods.

[25]Volden, Wiseman and Wittmer (2016) identify women's issues as those that "women in Congress are more likely than men to raise," and that women raise "in a greater volume" than men (5). Using the *Policy Agendas Project*, they classify all bills into 19 major topic areas. They find six topics in which significantly more bills are introduced by women than by men: (1) Health, (2) Labor, Employment, and Immigration, (3) Housing and Community Development, (4) Civil Rights and Liberties, (5) Education, and (6) Law, Crime, and Family.

[26]Although there are a variety of ways to operationalize this concept, we used the *Congressional Quarterly* (*CQ*) measure because the major bills it highlights also typically receive more media coverage than non-*CQ* bills, which should in turn bolster the potential electoral benefits of speaking on the issue.

[27]We further note that neither the number of `Women's Bills` nor `CQ Bills` is meaningfully associated with female vocal pitch. Although the correlation between women's vocal pitch and these measures is statistically significant ($t = -2.42$, $df = 61888$, $p < 0.05$ and $t = 5.82$, $df = 61888$, $p < 0.05$), the magnitude of the relationship is so small that we do not find it to be substantively compelling. We found a slightly

Table 5: The Quantity and Intensity of Women's Speech Affects the Quantity of Men's Speeches About Women

	Dependent variable:	
	"Women" Mentioned	
	(1)	(2)
Fixed Effects		
Constant	−2.695***	−2.237***
	(0.041)	(0.220)
Female Speeches	0.056***	0.060***
	(0.003)	(0.003)
Female Pitch	−0.124***	−0.129***
	(0.031)	(0.032)
Democrat		−0.334
		(0.250)
DW - Nominate		−0.525**
		(0.231)
Seniority		−0.012***
		(0.004)
Committee Chair		0.015
		(0.077)
White		−0.180
		(0.147)
Women Bills		−0.022
		(0.028)
CQ Bills		−0.065**
		(0.030)
One Minute		−1.029***
		(0.051)
Duration		0.086***
		(0.004)
Election Year		0.136***
		(0.034)
Female Speeches × Female Pitch	0.009	0.011**
	(0.005)	(0.006)
Random Effects		
MC	0.424	0.424
	(0.063)	(0.057)
N_1	50,235	50,235
N_2	509	509
Log Likelihood	−14,735.510	−13,950.230
AIC	29,481.010	27,930.460

Note: Dependent variable equals 1 if the speech included any of the Pearson and Dancey (2011*b*) women's dictionary terms, 0 otherwise. These models report the results from a multilevel logistic regression. All models also include a randomly varying intercept for each member of Congress. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Our results are in line with what we would expect if women's speeches influence male legislators' discussion of women. Though the interaction term in Model 5.1 is not statistically significant at the 0.05-level, calculating predicted probabilities suggests that vocal pitch can have a substantively meaningful effect on whether a male MC mentions women in his speech, particularly when large numbers of female MCs give emotionally intense speeches. Introducing controls (see Model 5.2) strengthens this interaction effect and also indicates that this relationship holds even after accounting for individual speakers' characteristics and the types of bills on the agenda.

To assess the substantive significance of our finding, Figure 1 plots the predicted values from Model 5.2. The x-axis shows the range of our `Female Speeches` variable (from 0 to 43). The y-axis plots the likelihood that a male MC's speech includes at least one Pearson and Dancey (2011*b*) term. We show average `Female Pitch` set to 2 standard deviations above and below its baseline in the solid and dashed lines, respectively.

From this figure, it is clear that as more female MCs take to the floor to give emotionally intense speeches about women, their male colleagues become more likely to mention women in their own speeches. For example, when `Female Pitch` is two standard deviations above its mean, going from the minimum number of female speeches referencing women (0) to the maximum (43) results in an increase in the likelihood that male MCs mention women from 0.05 to 0.56. Yet, it is important to note that such an effect only occurs when the number of female speeches becomes quite large. Going from one standard deviation below (6) to one standard deviation above (11) the mean number of female speeches, yields only a 3% gain in the likelihood of a male MC referencing women (from 0.07 to 0.10). This underscores the hurdles female lawmakers face when trying to advance women's issues in the U.S. House of Representatives.[28]

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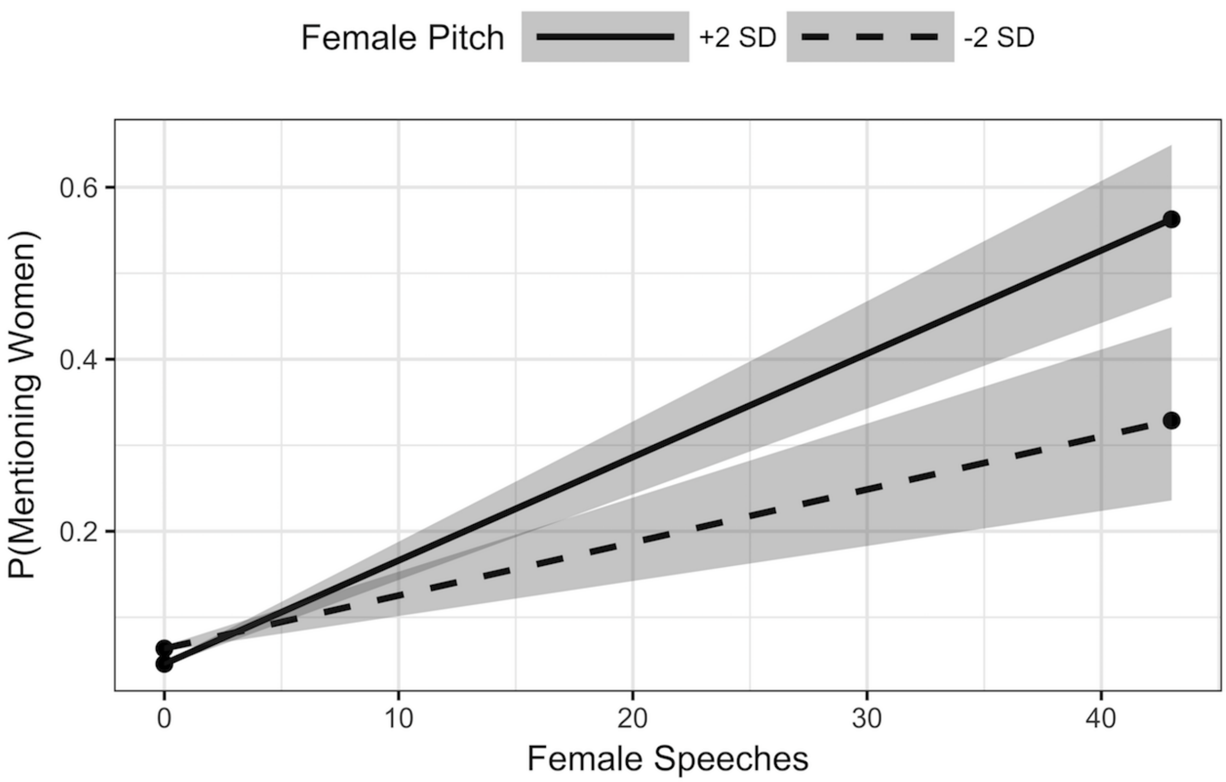
larger—yet still substantively small—correlation between our two bill measures and the number of female speeches delivered ($\rho = 0.14, 0.08$ for `Women's Bills` and `CQ Bills` respectively). We take this as evidence that changes in the amount and intensity of women's speeches about women are not primarily driven by variations in the legislative agenda.

[28]We re-estimated the models presented in Tables 1, 5, 6, and 7 restricting our data to observations of

Figure 1: The Quantity and Intensity of Women's Speech Affects the Quantity of Men's Speeches About Women



Note: Predicted male speaking behavior from Model 2 in Table 5 holding all other variables constant. Solid and dashed lines indicate `Female Pitch` was set to two standard deviations above (1.41) and below (-1.28) the mean respectively. On the x-axis `Female Speeches` is allowed to vary from its minimum (0) to maximum (43). The y-axis is the probability that the male speech included any of the Pearson and Dancey (2011*b*) women's dictionary terms. The gray ribbons represent 90 percent confidence intervals. The 95 percent confidence intervals overlap until the x-axis reaches approximately 25 speeches.

We next turn to investigating whether women's speeches might also influence the emotional intensity of male speeches referencing women. Here, the main dependent variable is the vocal pitch of male MCs who spoke on the same day as women, scaled to standard deviations above and below their baseline. We are primarily interested in the interaction between (1) the number of female speeches using any of the Pearson and Dancey (2011*b*)'s terms (`Female Speeches`), (2) the average vocal pitch of those speeches (`Female Pitch`), and (3) whether a male MC mentioned women (`"Women" Mentioned`). If women's speeches increase not only the quantity, but also the emotional intensity, of male references to women, then we would expect this interaction term to be positive and statistically significant.

In Model 6.1, the interaction term is positive and statistically significant at the 0.05-level. To help interpret this result, we present predicted values in Figure 2. When average female vocal pitch is set to two standard deviations above the mean (1.41), increasing the number of female speeches mentioning women from one standard deviation below the mean (6) to one standard deviation above the mean (11) raises men's predicted vocal pitch when talking about women from 0.17 standard deviations to 0.26 standard deviations above their baseline. Increasing the number of female speeches mentioning women from the minimum (0) to the maximum (43) raises men's predicted vocal pitch when talking about women from 0.12 standard deviations to 1.79 standard deviations above their baseline. This suggests that when female MCs deliver a large number of speeches on women with higher vocal pitch, male MCs are not only more likely to mention women, but also do so with increased emotional intensity.[29] These results hold even after the addition of a number of controls for legislator

vocal pitch ± 2 standard deviations from a speaker's baseline. These results can be found on pages S66–S69 in the SI. Our results are generally robust to the elimination of extreme observations of vocal pitch.

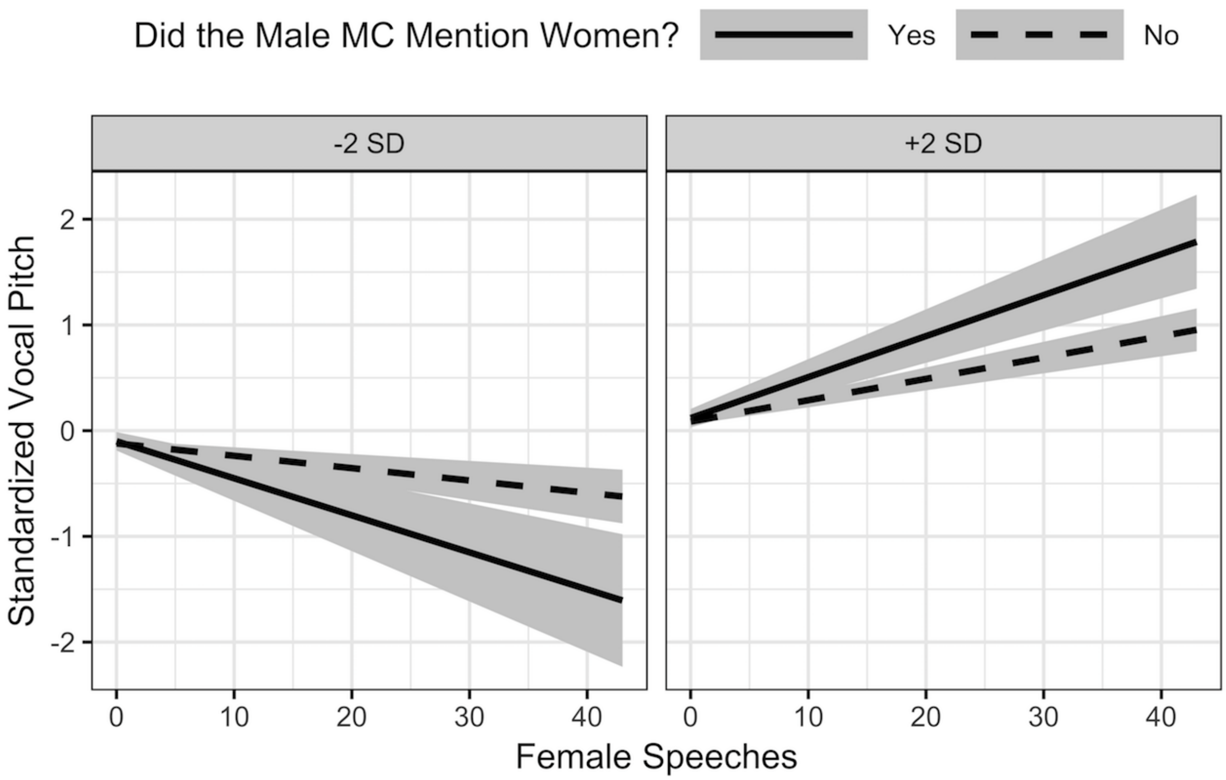
[29]Since the majority of women in Congress are Democrats – and Democratic men may have more incentive to appeal to female voters (e.g., Chaturvedi, 2016) – it is plausible that our results are contingent on male MCs' party. When we estimate separate models for Republican and Democratic men, however, we find that the speaking behavior of female lawmakers has a consistent effect on both groups of male MCs. This suggests that our results cannot be attributed to a single party (please refer to Section S7 in the Supplemental Information for additional details). At the same time, we acknowledge the possibility that only certain kinds of Republican (and Democratic) men are willing to engage with "women's issues," and that these male lawmakers may respond similarly to female MCs' speeches.

Table 6: The Quantity and Intensity of Women's Speech Affects Men's Vocal Pitch

	Dependent variable:
	Male Vocal Pitch
Fixed Effects	
Constant	-0.022^{***}
	(0.007)
"Women" Mentioned	0.026
	(0.022)
Female Speeches	0.003^{***}
	(0.001)
Female Pitch	0.077^{***}
	(0.009)
"Women" Mentioned × Female Speeches	-0.003
	(0.003)
Women" Mentioned × Female Pitch	0.004
	(0.031)
Female Speeches × Female Pitch	0.012^{***}
	(0.002)
"Women" Mentioned Female Speeches × Female Pitch	0.016^{***}
	(0.005)
Random Effects	
MC	0.000
	(0.000)
N_1	49,914
N_2	506
Log Likelihood	$-70,478.580$
AIC	140,977.200

Note: The dependent variable is the speaker's vocal pitch in standard deviations above or below the speaker's baseline. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

Figure 2: The Quantity and Intensity of Women's Speech Affects Men's Vocal Pitch



Note: Predicted vocal pitch derived from Model 2 in Table 6 holding all other variables constant. Solid lines indicate the speech included at least one of the Pearson and Dancey (2011*b*) women's dictionary terms. Dashed lines indicate all other speeches. For a given legislative day, `Female Speeches` is the total number of female speeches that used any of the Pearson and Dancey (2011*b*) women's dictionary terms and `Female Pitch` is the average vocal pitch of those speeches. `Female Speeches` is allowed to vary from the minimum (0) to maximum (43), whereas `Female Pitch` is set to two standard deviations above (1.41) and below (-1.28) the mean in the left and right panel respectively. The gray ribbons represent 95 percent confidence intervals.

characteristics and the legislative agenda (see Table S14 on page S37 in the Supplemental Information). Together this provides strong suggestive evidence of the link between female MCs' emotionally intense speeches about women and male MCs' speaking behavior.

Voting Behavior

Our results thus far are consistent with male MCs talking more about women, and with greater emotional intensity, when female lawmakers deliver a large number of emotionally intense speeches referencing women. On the one hand, these findings may represent (some) male legislators' desire to speak to women's concerns. In both judicial settings (Boyd, Epstein and Martin, 2010) – and in deliberation more generally (Karpowitz and Mendelberg, 2014, 288) – when women talk, men listen. This can, in turn, alter group behavior and decisions. On the other hand, men's behavior could also reflect a backlash against female MCs' speeches. Past research has shown that as women become more prevalent in legislatures, male politicians act to minimize their influence in order to maintain dominance (Heath, Schwindt-Bayer and Taylor-Robinson, 2005; Krook, 2015; Kanthak and Krause, 2012), including becoming more aggressive and controlling of deliberation (Kathlene, 1994). In this way, when female MCs take to the floor to deliver emotionally intense speeches, it could signal to male legislators that their dominance is under threat and thus result in an adverse reaction. We provide a preliminary examination of men's voting behavior in order to investigate whether changes in male MCs' speaking patterns can be better characterized as supportive of, or a backlash against, women's speech. To do so, we construct a measure of whether those Congressmen referencing women became more or less likely to vote with female MCs' who spoke about women on the House floor.

Estimating the relationship between women's speech and men's voting behavior is inherently difficult, as male legislators may be more likely to vote with female MCs who gave emotionally intense speeches about women simply because of shared ideology or partisanship.[30] To overcome this challenge, our dependent variable in the models presented in Table 7 scales the proportion of male MC votes cast with female speakers based on their previous shared voting behavior. Our measure includes three components: (1) the proportion of votes male MCs cast in the same direction as the female speakers on a given legislative day, (2) the proportion of votes those male MCs typically cast with those same female speakers on all previous legislative days, and (3) the degree to which those proportions vary. Combining these three pieces of information yields a standardized measure where positive values indi-

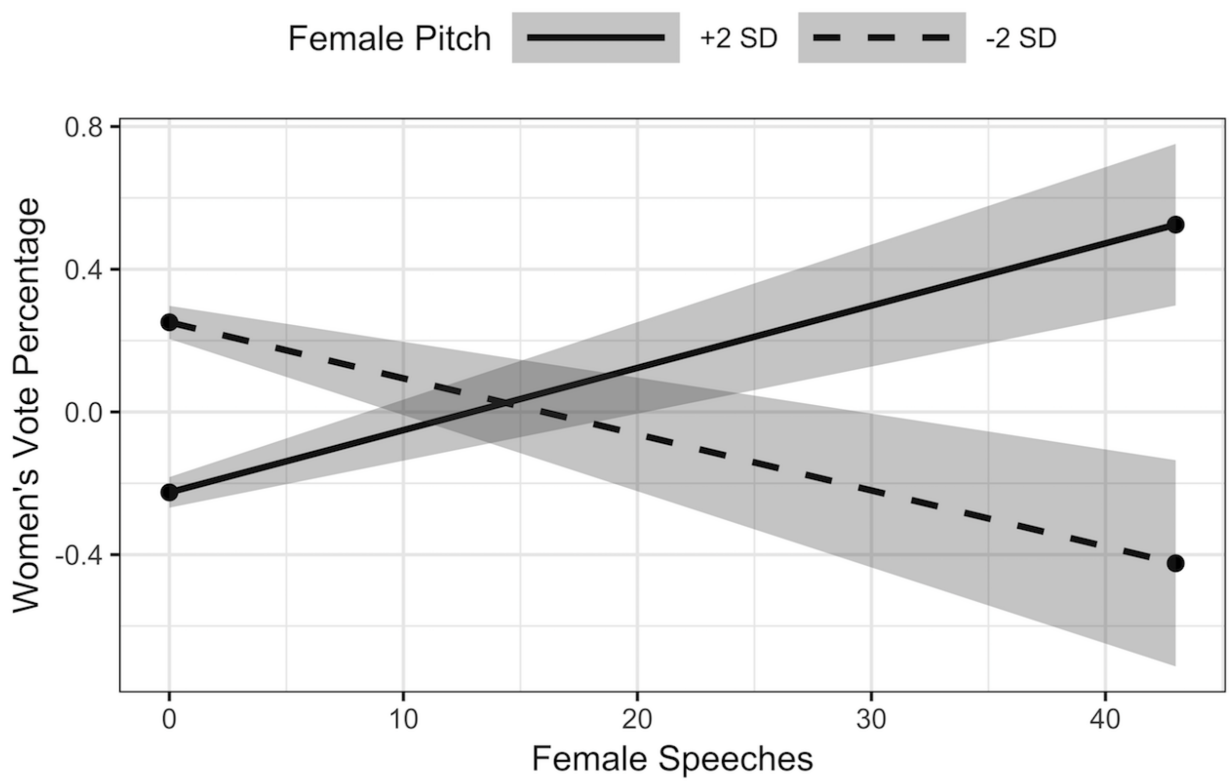
[30]We attempt to address this concern in our placebo tests, which are reported in Tables S29 and S30 on pages S60 and S62 in the Supplemental Information.

Table 7: The Quantity and Intensity of Women's Speech Affects Men's Voting Patterns

	Dependent variable:	
	Male Votes Cast	
	(1)	(2)
Fixed Effects		
Constant	0.019	0.162^{**}
	(0.015)	(0.079)
Female Speeches	0.001	0.0001
	(0.001)	(0.001)
Female Pitch	-0.187^{***}	-0.177^{***}
	(0.013)	(0.013)
Democrat		-0.094
		(0.091)
DW - Nominate		-0.078
		(0.084)
Seniority		-0.002
		(0.001)
Committee Chair		0.072^{**}
		(0.029)
White		-0.055
		(0.051)
Women Bills		0.058^{***}
		(0.010)
CQ Bills		0.001
		(0.012)
One Minute		0.018
		(0.014)
Duration		0.0001
		(0.002)
Election Year		-0.102^{***}
		(0.013)
Female Speeches × Female Pitch	0.015^{***}	0.012^{***}
	(0.002)	(0.002)
Random Effects		
MC	0.046	0.046
	(0.001)	(0.001)
N_1	21,920	21,920
N_2	485	485
Log Likelihood	$-28{,}122.730$	$-28{,}106.130$
AIC	56,257.460	56,244.270

Note: Outcome is the proportion of time male MCs voted with women, as described on page 38. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

Figure 3: The Quantity and Intensity of Women's Speech Affects Men's Voting Patterns



Note: Predicted male voting behavior from Model 2 in Table 7 holding all other variables constant. Solid and dashed lines indicate `Female Pitch` was set to two standard deviations above (1.41) and below (-1.28) the mean respectively. On the x-axis `Female Speeches` is allowed to vary from its minimum (0) to maximum (43). The y-axis has the percentage of time the male MC voted with women, as described on page 38. The gray ribbons represent 95 percent confidence intervals.

cate that male speakers were more likely to vote in line with female speakers than their past voting history would predict. Negative values indicate that male speakers were less likely to vote in line with female speakers, and would thus provide evidence of a backlash effect among those men who spoke with emotional intensity about women. A detailed working example can be found on pages S36–S41 in the Supplemental Information. We also provide alternative model specifications that yield similar results on pages S41–S42.[31] Likewise, a dyadic estimation of this relationship (and accompanying placebo tests) can be found in Section S8.2 of the Supplemental Information which starts on page S55.

The results of our model predicting male voting behavior can be found in Table 7. Since our primary variable of interest is the interaction term between `Female Speeches` and `Female Pitch`, we plot predicted percentage of co-voting in Figure 3. Model 7.2 shows a positive and statistically significant relationship between this interaction and the percentage of votes male MCs cast with female speakers. This provides evidence consistent with male legislators becoming more likely to vote with their female counterparts when women give a large number of emotionally intense speeches about women. When female MCs' average vocal pitch is set to two standard deviations above the mean (1.41) and women's speeches on women range from the minimum (0) to maximum (43), the rate at which male MCs vote with women on a given day increases from 0.23 standard deviations below to 0.53 standard deviations above what we would expect given past voting behavior.[32]

Together, these results hint at the importance of women's collective speaking efforts. In the 111th-113th Congresses, there were between 77 and 81 women in the U.S. House. The maximum number of female speeches we observe in our data (43) thus represents 56% of all women in the legislature taking to the floor to reference women. When we observe this high

[31]Unfortunately, we cannot say for sure whether votes take place after speeches. This is because there are no publicly available time stamps associated with specific votes. For example, *Voteview* data only include the date and vote number, not the time of day the vote occurred.

[32]We also estimated separate models for Democrats and Republicans. Table S21 reports these results on page S49 in the Supplemental Information. Predicted values are also plotted in Figure S11 which can be found on page S50. Collectively, these show that our general results hold within both parties.

degree of women's participation, our models suggest that we are also likely to see men talk more (and with greater intensity) about women. And, our preliminary evidence indicates that they may be more likely to vote in line with those female speakers. This suggests that increasing women's descriptive representation in legislatures, particularly by electing female candidates who are champions of women, could help female representatives further advance the interests of women among their male colleagues.

At the same time, two caveats are in order. First, given the observational nature of our data, we do not claim that these findings reflect a causal relationship. Indeed, our aim is not to make claims about the effect of female MCs' emotionally intense speeches about women on men's voting behavior, but instead to simply determine whether men's heightened vocal pitch represents a backlash effect. Our examination of voting behavior yields no evidence of male backlash, which suggests that when Congresswomen speak with greater intensity about women, they do not encounter any immediate detrimental consequences. More generally, although we find an association between women's speeches and male MCs' behavior—and present dyadic models and placebo tests that lend further support to this relationship (see Section S8.2 of the Supplemental Information)—legislators' speeches on women simply cannot be randomly assigned. We thus cannot definitively rule out alternative explanations for this relationship.

Second, it is important to note that at lower levels of female floor participation, we see no positive (and sometimes negative) estimates of the effect of women's emotionally intense speech. This finding in some ways echoes the broader literature on gendered speaking behavior. Research focusing on ordinary citizens finds that women speak in a way that is characterized as more feminine than men, which includes speaking with more emotional content (Hogg, 1985). Importantly, in mixed-gender settings, women often speak less than men (Karpowitz and Mendelberg, 2014) and are perceived as less influential than their male counterparts (Carli, LaFleur and Loeber, 1995). Though there are important differences in elite women's speaking behavior as compared to ordinary citizens, our results suggest that when speaking alone, or in small numbers, Congresswomen may also find it difficult to achieve the standing and influence necessary to affect their male colleagues' behavior. Building on our preliminary findings, future work should thus explore the broader consequences of women's collective legislative efforts.

Conclusions

Despite the growth of research using text-as-data approaches, audio data has received scant attention from political scientists. Yet, audio archives are available for a growing number of legislative chambers, including some state legislatures and city councils in the United States and national assemblies abroad. Similar data also exist in other political settings, from courts and public hearings to candidate debates. Our work represents the first effort to harness this growing corpus of audio data to ask and answer questions about legislators' speech. In focusing our attention on vocal pitch and emotional activation, our findings provide new insights concerning both the emotional intensity of U.S. lawmakers' speech and gendered speech dynamics. By highlighting the utility of audio-as-data approaches, we draw attention to a new way of studying political speech more broadly.

We argue that non-verbal components of legislators' floor speeches – in particular, small changes in a speaker's vocal pitch that are difficult to control – can shed new light on MCs' emotional intensity around a given issue area. Drawing on the well-established theoretical and empirical link between women's descriptive representation and activity on behalf of women, we focus on legislative speech addressing women as an ideal application of our approach. Using almost 75,000 floor speeches given in the U.S. House of Representatives, we show that women in Congress are not only more likely to discuss women on the floor, but also do so with greater emotional intensity. Our research thus both underscores, and also extends our understanding of, the importance of descriptive representation in legislatures. Though male MCs can and do represent women in Congress, female legislators are able to speak about women in a way that male lawmakers generally do not.

Our central finding suggests that small changes in vocal pitch can capture important information about legislators' emotional intensity. Our secondary analyses both indicate that increased vocal pitch is consistent with legislators' issue commitments and also draw attention to possible effects of emotionally intense speech. In our first extension, we offer two studies that provide important initial evidence that changes in vocal pitch correspond to other aspects of legislators' behavior. We show that the Congresswomen who are most emotionally activated when talking about women also receive significantly higher evaluations from women's interest groups as compared to the least activated female MCs. And, we show that Democrats and Republicans in Congress tend to become more emotionally activated when discussing policy issues owned by their respective parties. Taken together, these findings indicate that the emotional intensity legislators display in their floor speeches is not arbitrary, but is instead related to their underlying connection to the policy issue under debate. Extending our work further, our second set of extensions suggest that legislators' emotionally intense speech may have a broader impact in the legislative chamber. There is a positive correlation between large numbers of women taking to the floor to talk about women with intensity and male legislators discussing women (and doing so with greater intensity).

Clearly, the non-verbal content of legislative speech provides information that is not captured by more overt measures of lawmakers' attitudes or commitments. Changes in vocal pitch are not explained, for example, by partisanship or D-W NOMINATE scores. And, when we examine other behaviors—such as legislators' interest group scores and men's vocal pitch and voting behavior—vocal pitch is a significant explanatory variable even when we control for these measures. Audio data also provide an opportunity to uncover information from legislative speeches that is lost in text-as-data approaches. By incorporating vocal pitch into the study of legislators' behavior we gain information about the intensity (and perhaps impact) of representatives' words.

In highlighting vocal pitch as a measure of emotional intensity, our work also opens up new avenues of research with respect to legislative speech. Our extensions suggest that lawmakers that have long-standing commitments to a particular issue area tend to speak about that issue with higher vocal pitch. We expect that this logic could also apply to other groups of MCs. Veterans, doctors, and educators, for example, each likely draw heavily on personal experiences when discussing veterans' benefits, health policy, and education policy respectively on the floor of the U.S. House. Analyzing audio data from the legislative speech of those group members would further validate the results from this paper. More generally, the novel method and data that we advance provides a measure that can potentially separate those who feel intensely about a policy from those who are simply responding to district or party demands.

Our analyses, moreover, have only scratched the surface of what can be learned from audio data. In this paper, we focus on emotional intensity both because it is substantively interesting and also because our measure of emotional activation is well established in the psychology literature. Yet, much more information can be gleaned from this data. Political scientists, for example, are already studying raw vocal pitch (e.g., Klofstad, 2016). Scholars can also easily use audio data to examine other non-verbal measures. Researchers can analyze downward pitch contour as a proxy for disgust, as well as pitch variance within utterance (or total silence duration) as measures of anger.[33] Indeed, a variety of audio variables have been used to identify specific emotional states (Banse and Scherer, 1996). These measures, which can be computed from our data, could provide us with new perspectives on MCs' emotional reactions to their colleagues and to different issue areas. Moving beyond emotional intensity to measuring distinct emotional states would represent a significant step forward in the broader literature on emotions in politics.

An important future step for research involving audio data will be the development of tools to study vocal pitch at a more granular level than present techniques allow. Throughout our analyses, we have focused on mean fundamental frequency at the speech level. While much can be gained from this approach, matching audio data to text at the word level

[33]We thank an anonymous APSR referee for suggesting this point to us.

is an intriguing potential avenue of future research. Although segmenting audio data into individual words poses significant methodological challenges, early work by Dietrich, O'Brien and Yao (2019) posits interesting questions on intersectional identities that could benefit from more granular audio data.

Regardless of the results of this additional work, it is clear that floor speeches are an important tool for legislators. While it is easy to think of these speeches simply as collections of sentences and paragraphs, by examining the non-verbal behavior of MCs, we conceptualize the House floor as something more than words on a page. Our work allows scholars to view speeches as acts in which text, audio, and video come together to produce content that influences behavior within (and possibly beyond) Capitol Hill. Though speeches have long been acknowledged as valuable tools for understanding politicians' underlying ideological positions, we demonstrate that their non-verbal components yield insights into the intensity with which those positions are held.

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Supporting Information for: Pitch Perfect: Vocal Pitch and the Emotional Intensity of Congressional Speech

Contents

S1 Description of Floor Speech Data

In this section we describe the *HouseLive* video archives, as well as our approach to extracting the text and vocal pitch of legislators' floor speeches from these archives. We also outline our approach for analyzing legislators' vocal pitch.

S1.1 House Video Archive

We chose to use *HouseLive*[1] as our data source because of their easily accessible audio and video archives. To conserve space and reduce processing time, we use their `mp3` files instead of `mp4` files. In total, we downloaded 863 `mp3` files spanning from January 6, 2009 to August 4, 2014.

To identify both the speakers and text of floor speeches, we used the closed-captioning information provided by *HouseLive*. Unlike the *Congressional Record*, closed-captioning information has the advantage of reporting verbatim what is said on the House floor. One drawback to this approach is that since closed-captions are produced in real-time, typographical errors may be a concern. In email correspondence, the company that performs the closed-captioning service for the House of Representatives asserts that their transcribers are generally 95 percent accurate, meaning that 95 percent of the time the words that are transcribed are the words actually spoken on the House floor. This assessment is based on yearly evaluations, in which the company randomly selects a certain number of transcripts from each of their transcribers and determines the degree to which those transcripts capture the floor debate for that day. For this study, we transcribed 100 randomly selected speeches. When these speeches were compared to the closed-captioning information, regardless of the similarity measure one used, the closed-captions were essentially the same as the transcripts. Based on these results and our communication with the closed-captioning company, we are confident that the closed-captioning found on *HouseLive* is an accurate reflection of what is said in the U.S. House of Representatives.

The individual `mp3` files we collected averaged 7 hours and 27 minutes in length. Using the open-source software `ffmpeg`, we split these longer audio files into individual speeches using the time stamps found in the closed-captioning information and converted these into `wav` files. This resulted in 152,117 `wav` files. Due to the large number of extremely short speeches, we restricted our analysis to those speeches that had at least 50 words. This resulted in text and audio for 74,158 speeches.

[1] `http://houselive.gov/`

S1.2 Extracting Vocal Pitch

From this corpus of `wav` files, we used the software *Praat*[2] to extract vocal pitch.[3] This software implements the algorithm outlined by Boersma (1993). Similar to other algorithms that focus on time-domain periodicity, *Praat* estimates the fundamental frequency by dividing the autocorrelation of a windowed signal by the autocorrelation of the window itself. One must assume the signal is stationary within each window, which is why the algorithm divides the audio file into small segments (around 60ms), then takes the average.[4]

As explained in the main text (and below), women typically speak at a higher average vocal pitch than men. In order to make inferences across male and female MCs, one thus has to standardize each speaker's vocal pitch by their baseline. We accomplish this by subtracting the speaker's mean vocal pitch across all speeches from their pitch in a given speech and then dividing by the standard deviation of the speaker's pitch.[5] For example, Linda Sánchez's (D-CA) mean vocal pitch is 216.71Hz with a standard deviation of 26.35Hz. If she gave a speech with a vocal pitch of 250Hz, our standardized measure would be $\frac{250-216.71}{26.35} = 1.26$, suggesting for that speech her vocal pitch was a little over one standard deviation higher than her baseline.

After computing standardized vocal pitch measures for all available speeches, we added several additional controls. Party identification and ideology were obtained from *Voteview*. Race and seniority were obtained from *GovTrack*, and we identified committee chairs using the data provided by Stewart and Woon (2016).[6] We also included two dummy variables. One of these variables returns a 1 when the speech was given in an election year. The other variable returns a 1 when the speech was less than one-minute in length. Along these lines, we also included the length of the speech in minutes.

S2 Vocal Pitch and Emotional Intensity

One of the central claims of this paper is that vocal pitch can be used as an indicator of emotional intensity. Since this is a novel measure in political science, it is important to validate that pitch can, indeed, be used to measure emotional activation. To this end, in

[2]`http://www.fon.hum.uva.nl/praat`

[3]We extract vocal pitch using only voiced speech. Generally speaking, an utterance could be composed of (1) voiced speech, (2) unvoiced speech, and (3) silence. Although there is some debate over whether to use unvoiced speech when estimating the fundamental frequency (for review, see Hess 2007), for the most part scholars tend to use only voiced speech.

[4]Specifically, to use this software, one has to set five parameters: the pitch floor, pitch ceiling, window length, window shape, and voicing threshold. For the pitch floor and ceiling, we used *Praat* suggested settings, meaning for men, we set the pitch floor to 75Hz and the ceiling to 300Hz. For women, we used a pitch range of 100 to 500Hz. For both the window shape and voicing threshold we used the default settings.

[5]Author et al. (2017) also explain why standardization can help account for any unsystematic measurement errors associated with the algorithm used to extract the fundamental frequency.

[6]`http://web.mit.edu/17.251/www/data_page.html`

this section we provide a more thorough theoretical definition of emotional intensity and its link to pitch, and offer several validation exercises aimed at verifying that our measure of vocal pitch corresponds to changes in emotional intensity.

S2.1 The Circumplex Model of Affect and Vocal Pitch as a Measure of Emotional Activation

Our paper draws extensively from the work of James Russell (e.g., Russell 1980, 2003). The circumplex model of affect from that work posits that all affective states arise from two neurophysiological systems, one related to a pleasure-displeasure continuum (called "valence") and the other related to alertness (called "arousal" or "activation"). According to Russell (2003), at any given moment, one's emotional disposition is a single blend of these two dimensions. The horizontal dimension ranges from one extreme (e.g., agony) through a neutral point to its opposite extreme (e.g., ecstasy). For our purposes, we are interested in the vertical dimension, which ranges from a deactivated emotional state, such as being sleepy, to an activated emotional state, ultimately culminating in "frenetic excitement" (Russell 2003, 148). In the context of legislative speech, we call this "emotional intensity."

We offer vocal pitch as a reasonable measure of this arousal/intensity dimension. Specifically, in their review of emotional measurements Mauss and Robinson (2009) state:

> The assessment of vocal characteristics appears to be especially useful in understanding levels of emotional arousal, with higher levels of pitch and amplitude associated with higher levels of arousal (Table 1). By contrast, attempts to link emotional valence or discrete emotions to vocal characteristics have been met with mixed success at best, although more sophisticated methods may be capable of doing so in the future. Thus, we conclude that vocal characteristics are primarily reflective of the dimension of emotional arousal (225-226).

Generally speaking, the relationship between vocal pitch and emotional intensity is due to an automatic physiological reaction in which our muscles – including our vocal cords – naturally tighten when we are emotionally activated. According to Posner, Russell and Peterson (2005), when sensory stimuli are present, emotional arousal is likely relayed to the reticular formation (RF) through the amygdalorecticular pathways (Koch and Ebert 1993; Rosen et al. 1991). This broadly increases activity in the cerebral cortex (Heilman, Watson and Valenstein 2011; Jones 2003), which triggers changes in muscle tone and in the sweat glands (Jones 2003), both of which are associated with subjective ratings of emotional arousal (Lang et al. 1993). This increased blood flow to the muscles also causes vocal cords to contract naturally, raising the fundamental frequency (F_0) of one's voice.

Vocal pitch is not the only way to measure emotional intensity, nor is it the only audio variable that scholars should study. Rather, we simply suggest that vocal pitch is a reasonable measure of emotional intensity and should be seriously considered by those interested in both speech-as-data and audio-as-data approaches. We introduce vocal pitch as an important audio feature, especially for those interested in understanding elite emotional expression.

Although we believe vocal pitch can be an important measure for political scientists, we recognize that it will be unfamiliar to many in the field. For that reason, we offer here a number of validation exercises to justify the use of vocal pitch as a measure of emotional intensity. In the section that follows, we provide four additional validation exercises which collectively provide strong evidence that vocal pitch is measuring the activation dimension of Russell (2003)'s two-dimensional model.

S2.2 Additional Validation #1: Data from Goudbeek and Scherer (2010)

Our first validation exercise involves presenting some of the results from Goudbeek and Scherer (2010). In this study, the authors use the Geneva Multimodal Emotion Portrayals (GEMEP) corpus to understand how vocal characteristics are related to arousal and valance. The GEMEP corpus "contains a large set of systematically controlled portrayals of emotional expressions and is ideally suited for research on emotional response patterning" (Goudbeek and Scherer 2010, 1323). These include 12 emotional states grouped into "high" and "low" arousal and categorized as either "positive" or "negative" in valence, meaning actors were asked to portray twelve emotional states and Goudbeek and Scherer (2010) then categorized those emotions as being either an activated or deactivated emotional state.

It is important to note that in keeping with the literature, the data from Goudbeek and Scherer (2010) rely on actor portrayals of emotions. To create these data, trained actors are asked to portray different emotional states which the authors define as being either more or less intense. These actors are generally *not* specifically prompted to increase their vocal pitch. As explained in Bänziger and Scherer (2007), actors are provided with short definitions of the emotional states and scenarios they are to perform. For those concerned with the use of actor portrayals, Scherer (2013) examined the use of actor portrayals versus exogenous inducement of emotions. "[T]he data demonstrated that under both procedures (acted vs. induced emotions), the expression in the voice was almost the same on measures such as… F_0," as well as speech rate, energy, spectral, and temporal parameters." This "rejects the claim that acted or portrayed emotion expressions are artificial, exaggerated, and falsely prototypical when compared with induced emotional expressions" (Scherer 2014, 226).

As a validation exercise, we reprint the second panel of Figure 1 from Goudbeek and Scherer (2010), which provides strong evidence that mean vocal pitch is related to emotional intensity. As we show in Figure S1, their data demonstrate the relationship between vocal pitch and emotional intensity. In Panel A, we highlight high-intensity positive emotions, which include "Amusement," "Pride," and "Joy," in the grey box. The red line indicates the mean vocal pitch across these three emotions, and the red box identifies the lowest mean pitch (for "Pride"). In Panel B, we highlight low-intensity positive emotions, which

Table S1: The Twelve Emotions Included in Goudbeek and Scherer (2010) and Their Abbreviations

Arousal	Valence: Positive	Valence: Negative
High	Elation (joy)	Hot anger/rage (ang)
	Amusement (amu)	Panic fear (fea)
	Pride (pri)	Despair (des)
Low	Pleasure (ple)	Cold anger/irritation (irr)
	Relief (rel)	Anxiety/worry (anx)
	Interest (int)	Sadness/depression (sad)

Note: Reproduction of Table 1 from Goudbeek and Scherer (2010); boldface highlighting associated with high potency/control emotions added to aid interpretation.

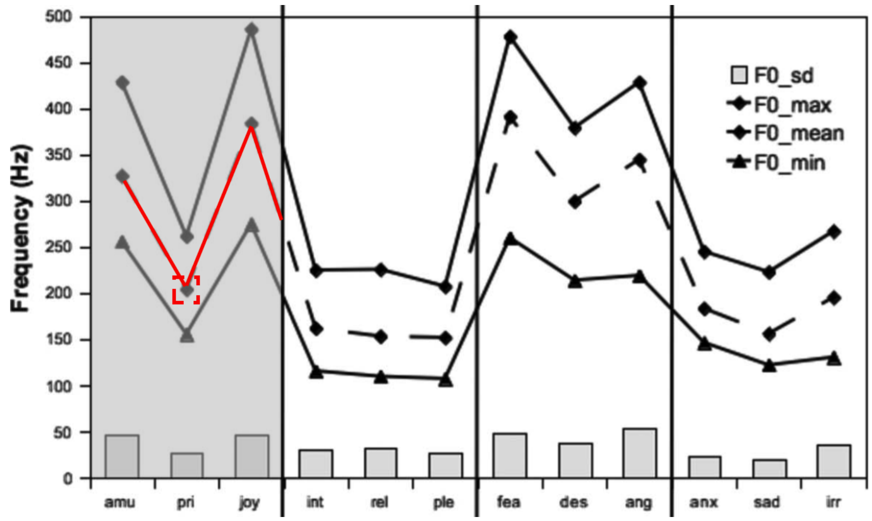
include "Interest," "Relief," and "Pleasure," in the grey box. The red line indicates the mean vocal pitch across these three emotions, and the red box identifies the highest mean pitch (for "Interest"). Comparing across these two panels, it is clear that the mean vocal pitch for these high-intensity positive emotions is consistently higher than the mean vocal pitch for low-intensity positive emotions. In fact, by comparing the lowest vocal pitch for high-intensity emotions with the highest vocal pitch for low-intensity emotions (identified with red boxes), we can see that the mean vocal pitch is *always* higher for these high-intensity emotions. This suggests that mean vocal pitch can reasonably discriminate between high- and low-intensity positive emotions.

In Figure S2, we demonstrate a similar finding for the mean vocal pitch for negative emotions. Here, again we re-print the second panel of Figure 1 in Goudbeek and Scherer (2010). In Panel A, we highlight the high-intensity negative emotions, which include "Fear," "Despair," and "Rage," in the grey box. The red line indicates the mean vocal pitch across these three emotions, and the red box identifies the lowest mean pitch (for "Despair"). In Panel B, we highlight the low-intensity negative emotions, which include "Anxiety," "Sadness," and "Irritation," in the grey box. The red line indicates the mean vocal pitch across these three emotions, and the red box identifies the highest mean pitch (for "Irritation"). As with positive emotions, we see that low-intensity negative emotions always have a lower vocal pitch than high-intensity negative emotions. Taken together, this provides strong evidence from past research that vocal pitch should offer some validity in assessing the intensity of emotions.

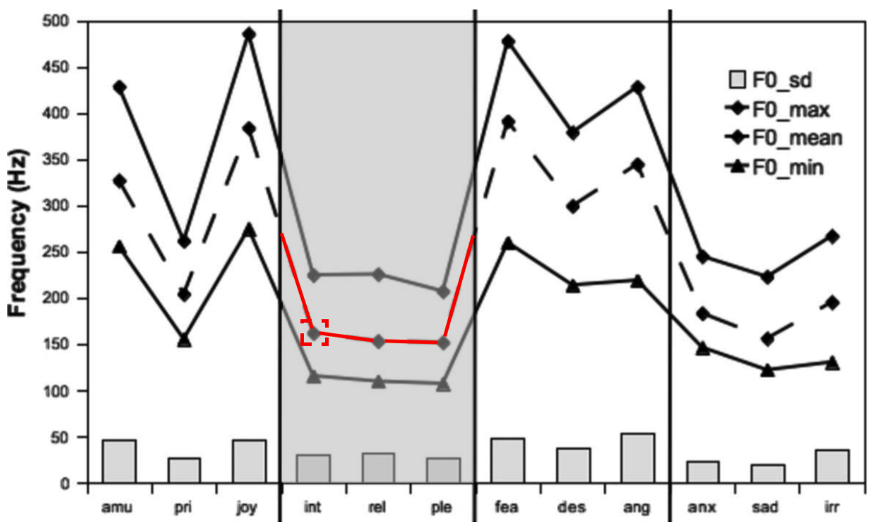
S2.3 Additional Validation #2: Data from Laukka (2004)

Our second validation exercise also uses actor portrayals. However, unlike GEMEP, Laukka (2004) considers only five base emotions: anger, disgust, fear, happiness, and sadness. He

Figure S1: Reproduction of Figure 1, Panel 2 from Goudbeek and Scherer (2010) (Positive Emotions)



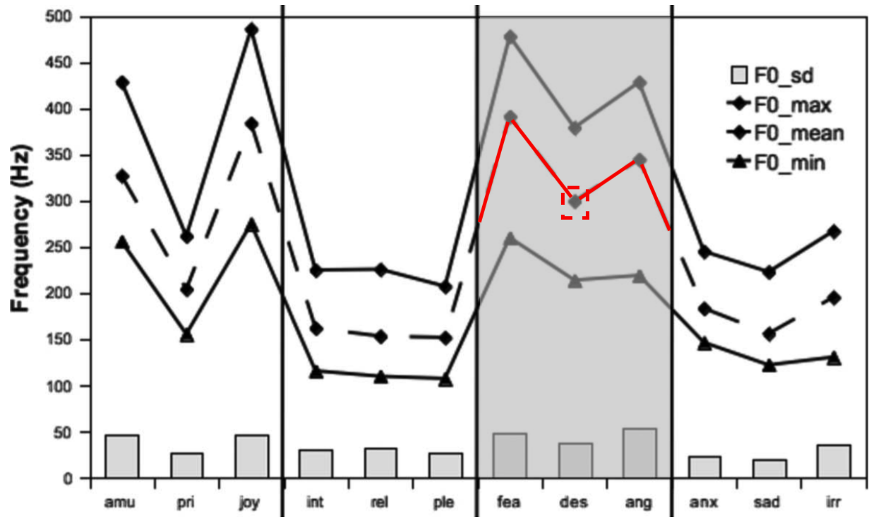
(a) High Intensity



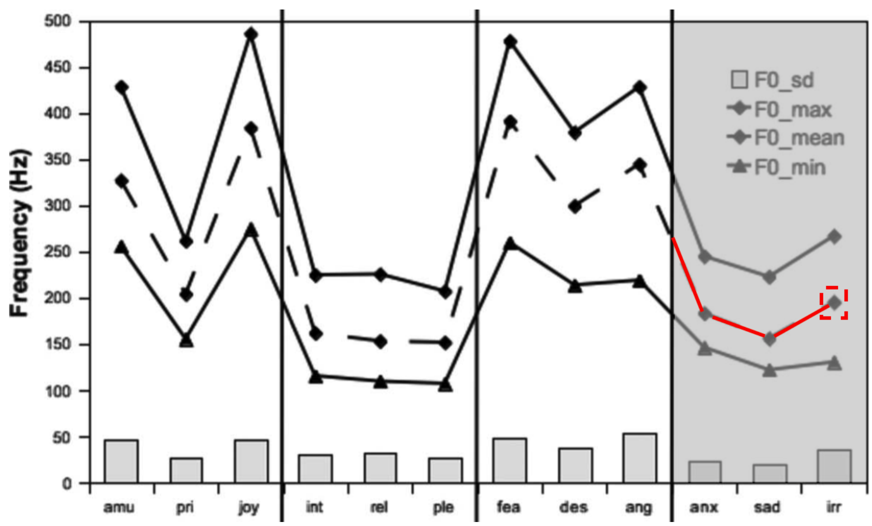
(b) Low Intensity

Note: Reproduction of Figure 1, Panel 2 from Goudbeek and Scherer (2010). Additional grey shading and red highlights added to aid interpretation. In Panel A, red highlighting indicates mean vocal pitch for high intensity positive emotions, with a red box indicating the lowest mean vocal pitch. In Panel B, red highlighting indicates mean vocal pitch for low intensity positive emotions, with a red box indicating the highest mean vocal pitch.

Figure S2: Reproduction of Figure 1, Panel 2 from Goudbeek and Scherer (2010) (Negative Emotions)



(a) High Intensity



(b) Low Intensity

Note: Reproduction of Figure 1, Panel 2 from Goudbeek and Scherer (2010). Additional grey shading and red highlights added to aid interpretation. In Panel A, red highlighting indicates mean vocal pitch for high intensity negative emotions, with a red box indicating the lowest mean vocal pitch. In Panel B, red highlighting indicates mean vocal pitch for low intensity negative emotions, with a red box indicating the highest mean vocal pitch.

measures emotional intensity by simply asking the actors to display anger with more/less intensity. This is distinct from Goudbeek and Scherer (2010), who asked actors to display "Rage" (high-intensity negative emotion) and "Irritation" (low-intensity negative emotion), yet the results are largely the same. More specifically, Laukka (2004) asks actors to vary their level of intensity, whereas Goudbeek and Scherer (2010) simply coded specific emotions as being either more or less intense.

Figure S3 reprints the first panel of Laukka (2004)'s Figure 1. Here, we show the mean vocal pitch when actors are asked to display "high" and "low" intensity emotions. Comparing Panel A to Panel B, it is clear that vocal pitch is significantly higher when actors are displaying emotions with "high intensity." Indeed, not only is the mean vocal pitch highlighted in Panel A always higher than the mean vocal pitch highlighted in Panel B, but none of the confidence intervals overlap. This provides additional evidence that vocal pitch can reasonably differentiate between more and less intense emotional expressions.

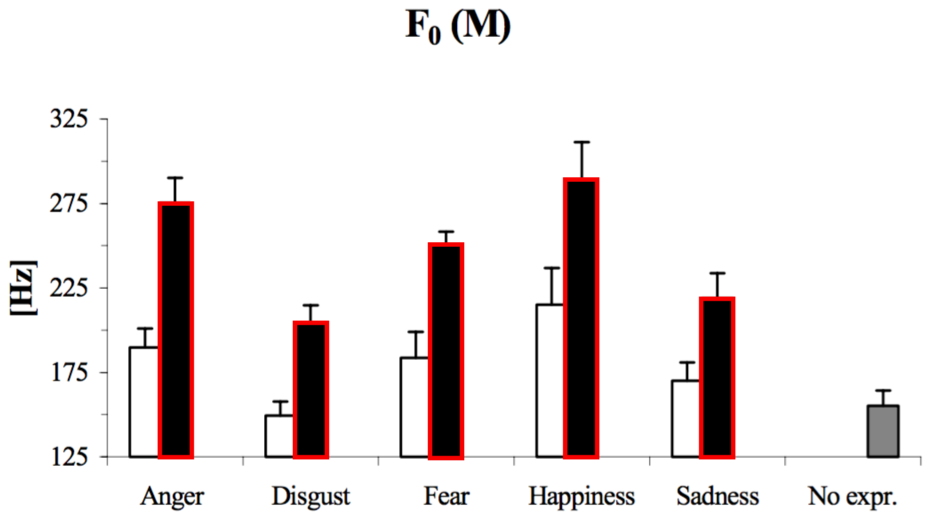
S2.4 Additional Validation #3: New Analysis of Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS)

In our third validation exercise, we analyze the Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS). This corpus contains 7,356 high-quality recordings of emotionally-neutral statements, spoken and sung with a range of emotions by 24 American male and female actors. The speech data consists of 8 emotional expressions: neutral, calm, happy, sad, angry, fearful, surprise, and disgust, each of which were delivered at two levels of emotional intensity: normal and strong. Similar to Laukka (2004), the actors were asked to vary their level of intensity prior to speaking, whereas Goudbeek and Scherer (2010) declared whether emotions were intense based on previous literature. Even though audio and video data is available, we restrict our analyses to the audio-only corpus, leaving us with 2,452 unique vocalizations. This valuable data set represents the most readily accessible source of a large number of unique emotional vocalizations. Perhaps more importantly, the emotional vocalizations have been validated by a team of 297 independent coders, making these data very well-suited for validating our measure of vocal pitch as an indicator of emotional intensity.

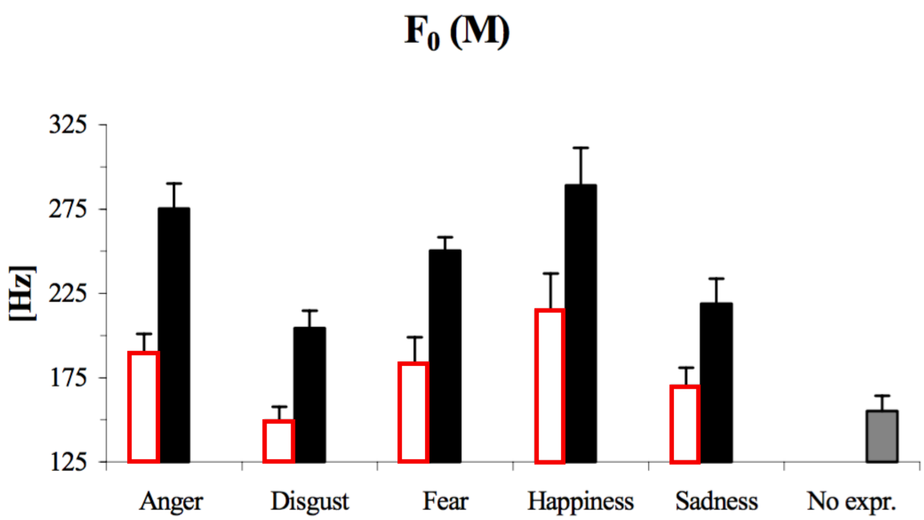
Our validation results can be found in Figure S4. Dark grey bars indicate the actor was portraying an emotion with strong (or high) emotional intensity, whereas light grey bars indicate the actor was asked to portray the same emotion with normal (or low) emotional intensity. We provide 95% confidence intervals for each estimate. Because women tend to speak at a higher vocal pitch than men, we also subdivided the data by male and female speakers.

Our findings are similar for both men and women. First, when all emotional categories are combined (bars labeled "All" and highlighted in red), high-intensity emotions are delivered at a significantly higher vocal pitch. This is the most important result for our study, since it provides additional corroborating evidence that mean vocal pitch can be used to

Figure S3: Reproduction of Figure 1, Panel 1 from Laukka (2004)



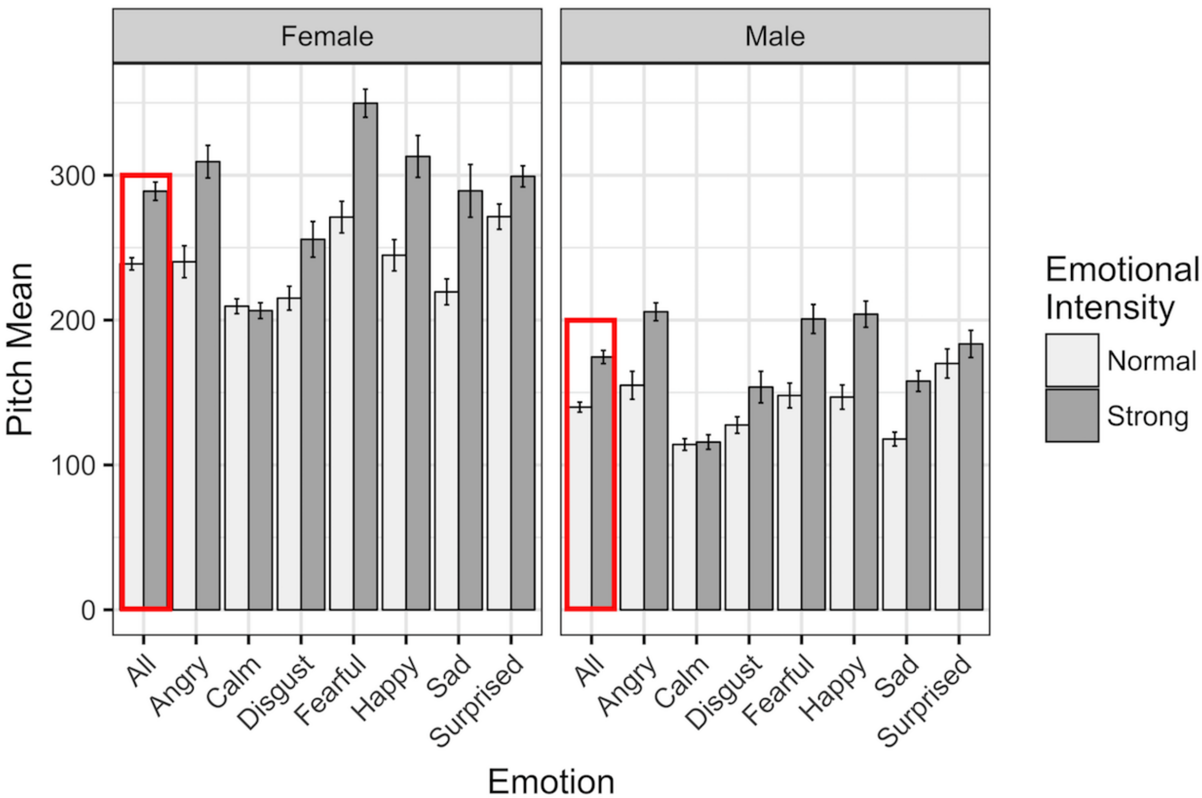
(a) High Intensity



(b) Low Intensity

Note: Reproduction of Figure 1, Panel 1 from Laukka (2004). Red boxes added to aid interpretation. In Panel A, red boxes indicate emotions expressed with high intensity. In Panel B, red boxes indicate emotions expressed with low intensity.

Figure S4: Emotions with "Strong" Intensity Delivered at a Higher Vocal Pitch Than Emotions with "Normal" Intensity (RAVDESS)



Note: Figure uses audio data from Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS). Light grey boxes indicate emotions displayed with "normal" intensity. Dark grey boxes indicate emotions displayed with "strong" intensity. Base emotions displayed on the x-axis. Red boxes highlight the trend across all emotions.

discriminate between different levels of emotional intensity. Second, vocal pitch is higher for high-intensity emotions in every category, except for "Calm." We think this is telling. Not only is it difficult to think of what "high intensity" calmness looks like, but Russell (2003) actually describes emotional activation as "frenetic excitement" (148). Given that, we contend calmness is essentially synonymous with a less activated emotional state which is why it is not surprising that the speakers conveyed the high and low versions of this emotion using similar vocalizations. Outside of calmness, vocal pitch is significantly higher across all the emotional categories when those emotions are delivered with high intensity.

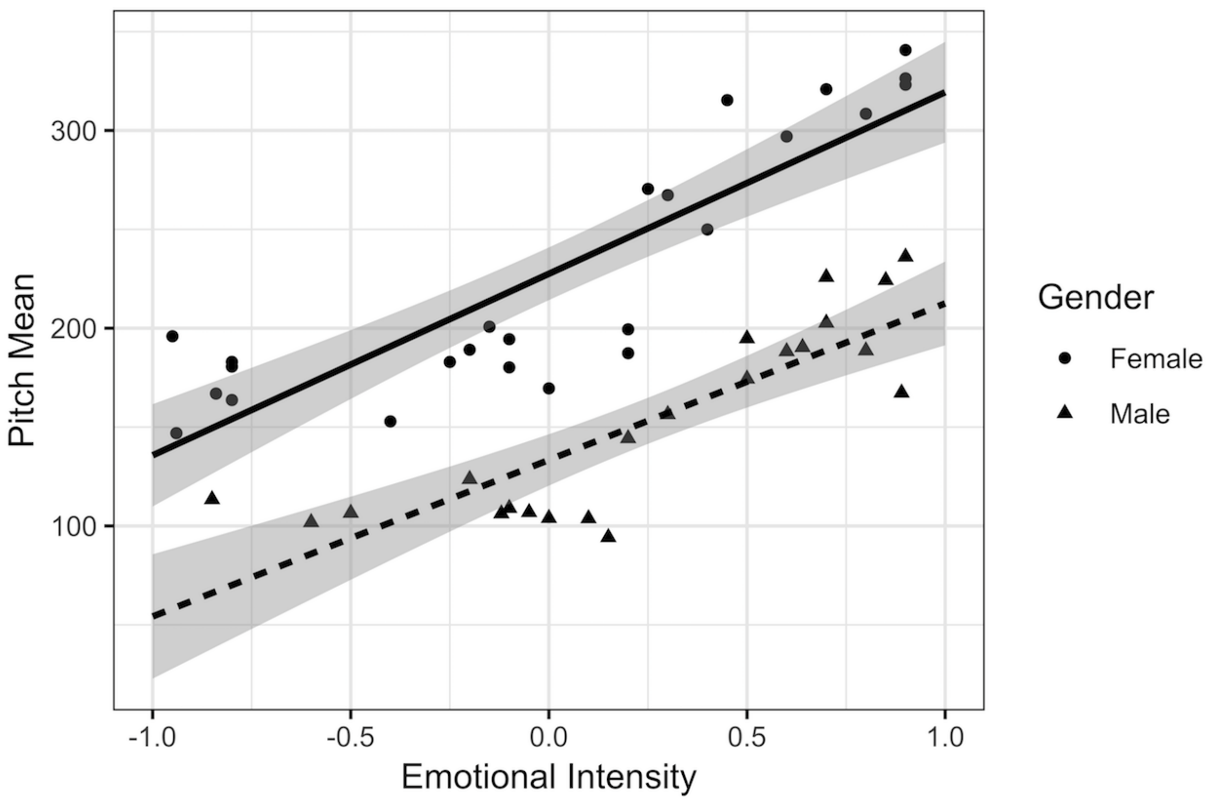
S2.5 Additional Validation #4: New Analysis of Giannakopoulos and Pikrakis (2014) Annotated Speaker Data

In our fourth validation exercise, we analyzed data provided by Giannakopoulos and Pikrakis (2014). This corpus consists of 47 audio clips collected from the Berlin Database of Emotional Speech.[7] Each clip is scored using a continuous scale ranging from low (-1) to high (1) emotional valence and activation which is distinctly different from both Goudbeek and Scherer (2010) and Laukka (2004). In terms of the former, Giannakopoulos and Pikrakis (2014) did not simply say discrete emotions were more/less intense, instead they had coders go through and listen to the audio files and code the degree to which the speaker was more/less activated. Similarly, unlike Laukka (2004) who asked actors to portray emotions with more/less intensity and then assume they did so, Giannakopoulos and Pikrakis (2014) actually code whether the speakers seem more/less activated when they are speaking. With that said, there is little information about the degree to which the coding of valence and activation have been validated. For this reason, these results should be viewed as a supplement to the validation exercises we report above.

Figure S5 displays the results of our analysis. The x-axis represents the emotional intensity of the recordings, as coded by Giannakopoulos and Pikrakis (2014). The y-axis represents the mean vocal pitch of these recordings as extracted by *Praat*. Circles represent emotional portrayals from male actors, and triangles represent portrayals from female actors. We also present the result of simple linear models in which mean vocal pitch is regressed on the level of emotional intensity separately by speaker sex, with grey bands representing the respective 95% confidence intervals. Not only does this plot show a strong linear trend, but emotional intensity is correlated with the mean vocal pitch at the 0.84 level for men ($t = 8.66, df = 23, p < 0.001$) and 0.87 level for women ($t = 7.04, df = 20, p < 0.001$). This data set supports our contention that vocal pitch can be used as an indicator of underlying emotional intensity. As with our previous validations, we consistently see higher mean vocal pitch when emotional intensity is higher. Moreover, mean vocal pitch is *not* significantly correlated with the valence dimension. This too was coded from negative (-1) to positive (1), but unlike emotional intensity there was no significant correlation found between emotional valence and mean vocal pitch ($t = 1.32, df = 45, p > 0.19$). This suggests that vocal pitch

[7] Unlike the RAVDESS data, these utterances are all German phrases.

Figure S5: Emotions with “Strong” Intensity Delivered at a Higher Vocal Pitch Than Emotions with “Normal” Intensity (Giannakopoulos and Pikrakis)



Note: Figure uses data provided by Giannakopoulos and Pikrakis (2014). Solid and dashed lines represent simple linear regression lines for male and female speakers, respectively. Perceived emotional activation (or intensity) is shown on the x-axis. This variable ranges from (-1) deactivated to (1) activated. The speaker's raw vocal pitch is shown on the y-axis.

is useful as an indicator of emotional intensity, rather than simply capturing valence (or positivity/negativity).

S2.6 Vocal Pitch: A Useful, but Not Exhaustive Measure

The analyses we present above demonstrate a consistent relationship between vocal pitch and emotional intensity (or activation). A reasonable concern, however, is that vocal pitch might also be influenced by the other dimension of emotions: valence. We are not arguing that there is absolutely no relationship between pitch and valence. Rather, we are arguing that pitch is more indicative of intensity than valence. This point has consistently been argued in the literature (e.g., Mauss and Robinson 2009). Thus, we feel safe in our assertion that vocal pitch can be used to measure emotional intensity.

Although we have shown vocal pitch to be a consistent indicator of emotional intensity, it is certainly not the only such indicator. We offer three reasons for the use of vocal pitch in our analysis over other measures. First, the present study is primarily interested in broadening audio-as-data approaches in political science. We use vocal pitch in order to achieve this end. Not only are there well-established theoretical arguments for what vocal pitch captures, but it is actually easy for researchers to use. Just as text analysis has a place for dictionary methods, audio analysis should have a place for specific features – like vocal pitch. Such features are not only theoretically interesting in and of themselves, but we must better understand those features before we begin to utilize more advance methods, like supervised and unsupervised learning algorithms.

Second, vocal pitch also has a well-established literature *within* political science. Scholars like Casey Klofstad (e.g., Klofstad 2016) have been working on understanding the role vocal pitch has to play in social science research for quite some time. These scholars have made considerable strides in understanding vocal pitch using small-n studies, but we are the first to apply such techniques to a large corpus of audio. Just as "all quantitative models of language are wrong – but some are useful," (Grimmer and Stewart 2013, 269) we view vocal pitch in a similar light, especially when it is used at scale. With large audio corpora, we can actually get a good sense of a speaker's baseline vocal pitch, which makes vocal pitch a much more useful measure because it can be scaled relative to what we expect.

Finally, "there is no globally best method for automated text analysis" (Grimmer and Stewart 2013, 270). We argue the same can be said for audio data. Indeed, much of the debate surrounding vocal pitch "can be resolved simply by acknowledging that there are different research questions and designs that imply different types of models will be useful" (Grimmer and Stewart 2013, 270). In this study, we are interested in understanding whether women exhibit higher vocal pitch when speaking about women and whether that seems to be generally good or bad for the advancement of women's interests. We think vocal pitch is a reasonable place to start this line of inquiry. Just as we hope this is not the last study on vocal pitch, this is not the only audio variable we plan to use in our own broader research agenda. In many ways, we view this study as the beginning, rather than the end,of audio-as-data approaches in the study of legislative speech, which is why the broader contribution is not vocal pitch, but the use of audio itself.

As an illustration of the important information contained in audio data that might be missed by text-as-data approaches, consider Figure S6, which shows two speeches from Rep. Rosa DeLauro. In the first speech (Panel A), Rep. DeLauro mentions "women" only once. In the second speech (Panel B), she references "women" eight times. Using existing measures, which would simply count references to women, we would conclude that the second speech is more women-focused than the first and move on. Using our method, in contrast, reveals that in the first speech Rep. DeLauro is speaking at 1.55 standard deviations above her baseline vocal pitch (i.e., with greater intensity), while in the second speech she speaks at her baseline. Investigating these speeches further, we find that in the first speech—which references women only once but was given with high intensity—Rep. DeLauro recalls her own experience with ovarian cancer and relates it to the experiences of other women who have been denied insurance because of a pre-existing condition. In the second speech, she is offering statistics related to women's health and the Affordable Care Act. Comparing these two speeches underscores the information lost when ignoring the non-verbal content of legislative speech.

S3 Descriptive Statistics

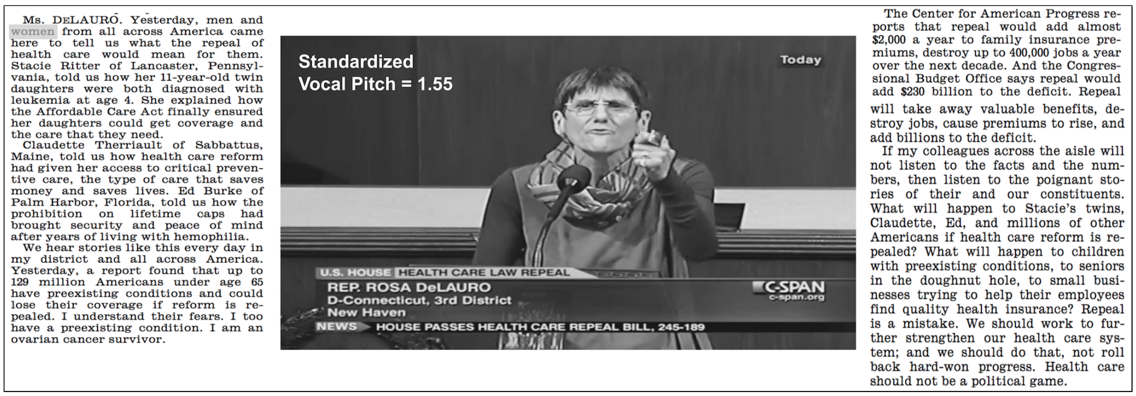
In this section, we report on several descriptive statistics on our measure of vocal pitch. Since women tend to speak at a higher vocal pitch than men, we subset our data by gender in the tables below.

S3.1 Male and Female MCs' Vocal Pitch when Speaking about Women

We first consider whether men and women in the U.S. House speak with higher vocal pitch when talking about women. To establish whether the speaker addressed women we create a binary variable indicating whether the speech used any of the Pearson and Dancey (2011*b*) dictionary terms related to women. These include "women," "woman's," "women's," "girl," "girl's," "girls," "girls'," "female," "female's," "females," "females'," "servicewoman," "servicewoman's," "servicewomen" and "servicewomen's." If a speech contains any of these terms it is coded as a 1, otherwise 0.

Beginning with Table S2, we report on the raw vocal pitch for men and women. We find male MCs did not speak with a significantly different vocal pitch when they were using one of the Pearson and Dancey (2011*b*) terms (t = 0.02, df = 58281, $p > .05$). This suggests that men do not tend to become more or less emotionally activated when talking about women. This is not the case for female MCs. Not only did they talk at a significantly higher vocal pitch when referencing women (t = 4.14, df = 12917, $p \leq .001$), but this result

Figure S6: The Importance of Vocal Pitch



(a) Rep. DeLauro More Emotionally Intense

(b) Rep. DeLauro Less Emotionally Intense

Note: In Panel A, we show a frame and the text from a speech delivered by Rep. DeLauro (D-CT) on January 19, 2011 in which she only mentions women once, but her vocal pitch suggests she is speaking more intensely about women. In Panel B, we show a frame and the text from a speech delivered by Rep. DeLauro on April 14, 2011 in which she mentions women eight times, but her vocal pitch suggests she is speaking less intensely about women. The Pearson and Dancey (2011*b*) dictionary terms are highlighted in grey.

Table S2: Average Vocal Pitch and Standard Deviation for Male and Female MCs by Party

	"Women" Mentioned		"Women" Not Mentioned	
	Pitch Mean	Pitch SD	Pitch Mean	Pitch SD
Male				
Republican	151.11	24.28	150.95	24.51
Democrat	151.94	24.29	152.17	25.65
All	151.50	24.28	151.49	25.03
Female				
Republican	207.02	30.27	203.11	30.52
Democrat	205.68	25.64	203.35	28.25
All	206.01	26.87	203.27	28.99

Note: Measurements of vocal pitch are in Hertz (Hz). In the first two columns, we restricted our data to speeches which used at least one of the terms outlined by Pearson and Dancey (2011*b*). In the last two columns, we restricted our data to speeches which did not use any of these terms. Rows correspond to indicated groups. For example, the average vocal pitch for all speeches delivered by Republican men mentioning women was 151.11Hz. Averages for each column can be found in the "All" rows.

holds across both Republican and Democratic women. Indeed, Democratic and Republican women tended to talk at 205.68Hz and 207.02Hz respectively when they spoke about women. Moreover, Democratic women's vocal pitch was lower when they were not using any of the Pearson and Dancey (2011*b*) terms ($t = 3.12$, df $= 8967$, $p \leq .01$), a result mirrored among Republican women ($t = 2.81$, df $= 3948$, $p \leq .01$). Taken together, this suggests that women in Congress of both parties tend to speak with higher vocal pitch when they are speaking about women.

In Table S3, we report on the same descriptive statistics as above, but using our measure standardized by a speaker's baseline vocal pitch. Positive values signify MCs are speaking above their mean or baseline vocal pitch. The first column shows female MCs speak at a significantly higher vocal pitch when using one of the Pearson and Dancey (2011*b*) terms, both compared to their baseline as well as compared to their male counterparts ($t = 3.01$, df $= 7484$, $p \leq .01$). Indeed, not only do Congresswomen tend to speak *above* their baseline when talking about women, they actually speak *below* their mean vocal pitch when they are not referencing women. This difference is highly significant ($t = 4.76$, df $= 12916$, $p \leq .001$), suggesting female MCs' vocal pitch increases when they reference women. The same cannot

Table S3: Average Vocal Pitch and Standard Deviation for Male and Female MCs (Standardized) by Party

	"Women" Mentioned		"Women" Not Mentioned	
	Pitch Mean	Pitch SD	Pitch Mean	Pitch SD
Male				
Republican	0.02	0.96	-0.00	1.00
Democrat	0.02	0.96	-0.00	1.00
All	0.02	0.96	-0.00	1.00
Female				
Republican	0.06	1.02	-0.01	0.99
Democrat	0.10	0.91	-0.02	1.01
All	0.09	0.93	-0.02	1.01

Note: For each MC, we converted vocal pitch to standard deviations above and below his or her average vocal pitch. In the first two columns, we restricted our data to speeches which used at least one of the terms outlined by Pearson and Dancey (2011*b*). In the last two columns, we restricted our data to speeches which did not use any of these terms. Rows correspond to indicated groups. Averages for indicated groups can be found in the "All" rows.

be said for male MCs, whose vocal pitch remains essentially unchanged when referencing women ($t = 1.34$, df $= 58278$, $p > 0.05$).

S3.2 Most and Least Emotionally Activated Female MCs

To identify the most and least emotionally activated MCs when talking about women, we first calculated the average vocal pitch when the legislator used at least one of the terms outlined by Pearson and Dancey (2011*b*). We also calculated the lawmaker's average vocal pitch when not using any of these terms. We then subtracted the latter from the former, yielding a measure which is positive when the MC spoke at a *higher than average* vocal pitch when using terms related to women.

In Table 3 in the main text, we report the 25 women in the U.S. House who were most/least emotionally activated when talking about women. We also show the average score those women received from 24 prominent women's groups obtained from *Project Vote*

Smart.[8] Our findings indicate women who speak with greater emotional intensity about women tend to receive higher scores from women's groups. This suggests that the heightened emotional intensity with which female MCs reference women is also reflected in their voting patterns.

Table S4 lists the 24 interest groups from *Project Vote Smart* we included to compute women's interest group scores. The *Project Vote Smart* group identification numbers and categories are listed in columns 1 and 2, respectively. All groups were listed under category 68, or "women" in the *Project Vote Smart* data. Column 3 reports the group name. Not only are these groups all the women's groups indexed by *Project Vote Smart*, but they are generally representative of the main groups that advance women's interests. Given that we used all *Project Vote Smart* women's interest groups, we view this as a fairly comprehensive list for this validation exercise. Please refer to Section in the main text for more discussion of these results and their broader implications.

S3.3 Most and Least Emotionally Activated Democrats and Republicans

In the main text, we also report on a validation of vocal pitch as a measure of emotional intensity by analyzing whether Democrats and Republicans are more emotionally intense on their party's "owned" issues (see Section). To investigate whether party members tended to be more emotionally intense on issues owned by their party, we created a dummy variable capturing whether the speech was a "party speech." To compute this, we first calculated the average proportion of a speech dedicated to party issues based on the closed captioning of the speech. These issues were identified using our STM, and are listed in Table S15. If a speech contained a greater proportion of party issues than the mean, then we coded it as a party speech (1). Otherwise, it was not considered a party speech (0). For all MCs, we calculated their mean vocal pitch when they were and were not giving a party speech. The difference between these indicates the extent to which MCs were emotionally intense when giving party speeches, with positive values indicating MCs that were more emotionally intense in speeches on their own party's owned issues.

As an additional analysis, we calculated each legislator's distance from the median DW-NOMINATE score for each party. We argue that those legislators closest to the party median should be most engaged with party-owned issues.

Table S5 lists the 25 most- and least-activated MCs when talking about party issues. In accordance with expectations, we find that the 25 legislators most activated when talking about party issues had an average DW-NOMINATE distance of 0.11 from their party median, compared to a distance of 0.19 for the 25 least activated legislators. Although this difference is slight, it is still statistically significant at the 0.05-level ($t = 3.24$, $df = 48$, $p < 0.01$). This general result holds for both Democrats ($t = 2.43$, $df = 30$, $p < 0.03$) and Republicans ($t =$

[8] `https://votesmart.org`

Table S4: Women's Interest Groups from *Project Vote Smart*

ID	Category	Group Name
164	68	American Association of University Women
38	68	American Congress of Obstetricians and Gynecologists
143	68	Business and Professional Women USA
134	68	Concerned Women for America
2154	68	Concerned Women PAC
1189	68	Emily's List
1343	68	Federally Employed Women
1906	68	Feminist Majority Political Action Committee
2332	68	Jewish Women International
1833	68	League of Women Voters
2493	68	LPAC
1930	68	Maggie's List PAC
1475	68	National Organization for Women
1654	68	National Women's Political Caucus
2340	68	Right Now Women PAC
1946	68	Susan B. Anthony List
671	68	The Woman Activist
319	68	United States Women's Chamber of Commerce
2243	68	Voices of Conservative Women
1860	68	Women Employed
1197	68	Women's Action for New Directions (WAND) and WILL
1910	68	Women's Campaign Fund
2339	68	Women Under Forty Political Action Committee
2336	68	Young Women's Christian Association (YWCA)

Note: List of all interest groups identified by *Project Vote Smart* as advancing women's issues. The full list can be found here: `https://votesmart.org/interest-groups/NA/68#.WuYGS9PwbVo` (Accessed on 4/29/2018).

1.96, $df = 16$, $p < 0.07$), even though the latter difference is only statistically significant at the 0.07-level. These results provide additional evidence that MCs become more emotionally intense when talking about issues to which we suspect they have deeper policy commitments. This provides another piece of predictive validity for our use of vocal pitch as an indicator of emotional intensity.

S4 Praat Floor and Ceiling

When estimating vocal pitch the most important *Praat* settings are the pitch floor and ceiling. Unfortunately, there is very little guidance in the literature about which settings should be used. For example, the *Praat* default is to set the pitch floor at 75Hz and the pitch ceiling at 500Hz, but the *Praat* online manual[9] also says "For a male voice, you may want to set the floor to 75 Hz, and the ceiling to 300 Hz," and "for a female voice, set the range to 100-500 Hz instead." We initially set our pitch floor and ceiling using the settings suggested by Re et al. (2012). They used a range of 50Hz to 300Hz for male voices and 100Hz to 600Hz for female voices. Based on this standard, we initially used a range of 50-600Hz to cover both male and female voices in earlier drafts of this manuscript. Upon further review, we decided to use the *Praat* suggested settings for our main analyses. This means we used a range of 75-300Hz for male MCs and 100-500Hz for female MCs. In order to ensure that our results are robust to the choice of pitch window, below we report on several replications of our results using alternative specifications of the minimum and maximum pitch settings in *Praat*.

S4.1 Replicating Results Using Three Different Pitch Windows

To eliminate the possibility that our results are dependent on choice of *Praat* settings, we re-estimated all of the models we report in the main text using different *Praat* window parameters. In these tables, the "Praat Default" column reports the results with a pitch floor of 75Hz and a pitch ceiling of 500Hz. The "Literature Suggested" column uses the range we used in our preliminary analyses (50-600Hz) and the "Praat Suggested" column uses a range of 75-300Hz for men and 100-500Hz for women. We find the results are substantively similar across these different *Praat* settings, suggesting our results are robust to different pitch windows.

Beginning with Table S6, we can see the substantive interpretation is the same when using any of the three settings. The results from Table 1 in the main text hold across *Praat* floor and ceiling choices.

Table S7 replicates the results from Table 5 in the main text using different *Praat* settings. The substantive interpretation of our results holds across settings. For the main effect of

[9] http://www.fon.hum.uva.nl/praat/manual/Intro_4_2__Configuring_the_pitch_contour.html

Table S5: Members of Congress Who Speak with Emotional Intensity About Party Issues Tend to Vote More With Their Party

(a) *Most* Activated

	Party Issue	No Party Issue	Pitch Diff.	|DW Diff.|
Name				
Sánchez (D-CA)	280.45	247.53	32.92	0.05
Carney (D-PA)	166.85	136.27	30.58	0.29
Wexler (D-FL)	202.62	173.03	29.59	0.00
Tauscher (D-CA)	220.03	192.17	27.86	0.10
Herrera (R-WA)	236.86	209.76	27.10	0.00
Meek (D-FL)	168.63	142.01	26.62	0.08
Holden (D-PA)	145.89	119.50	26.39	0.17
Napolitano (D-CA)	207.24	182.36	24.87	0.08
Roybal-Allard (D-CA)	209.44	188.53	20.91	0.01
Tiberi (R-OH)	152.14	131.24	20.89	0.08
Scott (R-GA)	165.65	145.42	20.23	0.04
Davis (D-IL)	137.95	117.80	20.15	0.06
Owens (D-NY)	173.91	153.82	20.09	0.23
Bonner (R-AL)	179.73	160.96	18.77	0.26
Schauer (D-MI)	151.64	133.03	18.61	0.06
Thompson (D-MS)	154.29	136.10	18.19	0.04
Bono (R-CA)	220.32	202.32	18.00	0.03
Wasserman (D-FL)	199.16	182.19	16.97	0.03
Amash (R-MI)	194.68	177.87	16.81	0.25
Myrick (R-NC)	225.12	208.92	16.20	0.04
Dingell (D-MI)	193.83	177.81	16.03	0.01
Kilpatrick (D-MI)	212.90	196.92	15.97	0.06
Rodriguez (D-TX)	150.02	134.16	15.86	0.11
Shuler (D-NC)	153.84	138.05	15.79	0.35
Lee (R-NY)	157.19	141.47	15.72	0.19
Groups				
All	186.41	165.17	21.24	0.11
Democrats	184.04	161.84	22.20	0.10
Republicans	191.46	172.24	19.21	0.11

(b) *Least* Activated

	Party Issue	No Party Issue	Pitch Diff.	|DW Diff.|
Name				
Amodei (R-NV)	133.02	160.13	-27.11	0.10
Murtha (D-PA)	147.66	174.50	-26.85	0.18
Green (D-TX)	155.33	181.73	-26.40	0.09
Cramer (R-ND)	153.89	175.37	-21.48	0.27
LoBiondo (R-NJ)	154.23	174.76	-20.54	0.25
Space (D-OH)	147.24	166.05	-18.81	0.25
Pomeroy (D-ND)	155.89	172.92	-17.02	0.18
Clarke (D-MI)	176.30	193.27	-16.97	0.08
Melancon (D-LA)	125.94	142.88	-16.94	0.24
Giffords (D-AZ)	204.09	220.54	-16.45	0.31
McHugh (R-NY)	107.96	123.97	-16.02	0.38
Cooper (D-TN)	106.02	121.33	-15.31	0.13
DelBene (D-WA)	181.40	196.69	-15.29	0.14
Adler (D-NJ)	141.06	156.33	-15.27	0.27
Heck (R-NV)	147.91	163.13	-15.23	0.08
Noem (R-SD)	212.15	227.20	-15.05	0.23
Cook (R-CA)	164.12	178.99	-14.87	0.12
Baird (D-WA)	132.08	146.79	-14.71	0.13
Moore (D-KS)	124.83	139.40	-14.58	0.18
Kelly (R-PA)	168.05	182.37	-14.32	0.29
Markey (D-MA)	154.66	168.85	-14.19	0.12
Gibson (R-NY)	141.05	155.21	-14.15	0.21
Miller (R-CA)	131.68	145.16	-13.48	0.13
Halvorson (D-IL)	237.54	251.01	-13.47	0.12
Peters (D-CA)	129.57	142.87	-13.29	0.25
Groups				
All	153.35	170.46	-17.11	0.19
Democrats	154.64	171.68	-17.04	0.18
Republicans	151.41	168.63	-17.22	0.20

Note: Measurements of vocal pitch are in Hertz (Hz). To make this table comparable to Table 3 in the main text, we created a dummy variable which equals 1 when a MC's speech contained more than the average number of party references. We called these "Party Speeches." In the first column, we restricted our data to party speeches. In the second column, we restricted our data to speeches which contained less than the average number of party references. The "Pitch Difference" column (abbreviated "Pitch Diff.") is the difference between these two columns. The 25 *most* (see Panel A) and *least* activated (see Panel B) MCs had the highest and lowest "Pitch Difference," respectively. The absolute difference between the MC's DW-Nominate score and the median DW-Nominate score for the MC's party is included in the "DW Difference" (abbreviated "DW Diff.") column. Higher values imply the MC's ideology was further away from the party median. Column averages for Democrats and Republicans can be found in the "Groups" section.

Table S6: Female MCs More Likely to Talk About Women, with Greater Intensity (Different Pitch Windows)

	Dependent variable:					
	Standardized Vocal Pitch					
	Praat Default Settings		*Literature Suggested Settings*		*Praat Suggested Settings*	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	−0.001	0.139***	−0.0004	0.128***	−0.002	0.151***
	(0.004)	(0.024)	(0.004)	(0.024)	(0.004)	(0.024)
Female	−0.020*	−0.033***	−0.020*	−0.033***	−0.017	−0.032***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
"Women" Mentioned	0.007	−0.064***	0.005	−0.064***	0.020	−0.054***
	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)	(0.014)
Female × "Women" Mentioned	0.110***	0.131***	0.111***	0.132***	0.090***	0.112***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Controls		✓		✓		✓
N_1	71,203	71,203	71,245	71,245	71,198	71,198
N_2	613	613	613	613	613	613
Log Likelihood	−100,726.400	−99,746.740	−100,786.400	−99,903.080	−100,720.100	−99,645.100
AIC	201,464.800	199,521.500	201,584.800	199,834.200	201,452.100	199,318.200

Note: Models are identical to Table 1, Models 3 and 4 except we use different Pratt settings. Control variables are excluded to save space Full models available upon request. The dependent variable is the speaker's vocal pitch in standard deviations above or below the speaker's baseline. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Table S7: The Effect of Quantity and Intensity of Women's Speech on Quantity of Men's Speeches About Women (Different Pitch Windows)

	Dependent variable:					
	"Women" Mentioned					
	Praat Default Settings		*Literature Suggested Settings*		*Praat Suggested Settings*	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	-2.693^{***}	-2.234^{***}	-2.695^{***}	-2.237^{***}	-2.692^{***}	-2.235^{***}
	(0.041)	(0.220)	(0.041)	(0.220)	(0.041)	(0.221)
Female Speeches	0.055^{***}	0.060^{***}	0.056^{***}	0.060^{***}	0.055^{***}	0.060^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Female Pitch	-0.121^{***}	-0.129^{***}	-0.124^{***}	-0.129^{***}	-0.127^{***}	-0.135^{***}
	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)
Female Speeches × Female Pitch	0.009^{*}	0.012^{**}	0.009	0.011^{**}	0.011^{*}	0.014^{**}
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Controls		✓		✓		✓
N_1	50,235	50,235	50,235	50,235	50,235	50,235
N_2	619	619	619	619	619	619
Log Likelihood	−14,735.990	−13,950.320	−14,735.510	−13,950.230	−14,735.630	−13,949.720
AIC	29,481.990	27,930.630	29,481.010	27,930.460	29,481.260	27,929.440

Note: Models are identical to Table 5, Models 1 and 2 except we use different Pratt settings. Control variables are excluded to save space. Full models available upon request. Dependent variable equals 1 if the speech included any of the Pearson and Dancey (2011*b*) terms, 0 otherwise. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

"Female Speeches" and "Female Pitch" the coefficients and levels of statistical significance are essentially unchanged, regardless of the pitch floor and ceiling, as is the interaction term between these two variables. Unlike the results we reported in our preliminary analyses using a pitch window of 50-600Hz, when either the *Praat* default or recommended settings are used the interaction term is statistically significant even when no controls are included. This suggests our results are quite robust to different pitch windows.

The robustness of our results is also shown in Table S8. Here, we replicated the results from Table 6 in the main text using three different *Praat* settings. Again, the results are largely the same. Again, this provides strong evidence that the results presented in the main text cannot be attributed to the *Praat* settings.

We find essentially the same results in Table S9 which replicates the results from Table 7 in the main text using different *Praat* settings. Again, we are primarily interested in the interaction between "Female Speeches" and "Female Pitch," which does not change substantially from one model to the next. It is always positive and statistically significant with a coefficient that only varies by 0.001 when different *Praat* settings are used. Altogether, these replications give us a high degree of confidence that our results are not sensitive to the selection of pitch windows within *Praat*.

S4.2 Replicating Results Using Multiple Permutations

The lack of empirical guidance in terms of the *Praat* floor and ceiling is one of the reasons why we emphasize mean vocal pitch in this study. Not only is vocal pitch a useful measure of emotional intensity, but Author (2018) demonstrates that it is also a fairly robust measure. Hess (2007) emphasizes the challenges of properly estimating the vocal pitch track, which is why summary measures can be especially useful. Unlike estimating a single value of the vocal pitch track (e.g., minimum), the mean and median are much more resistant to errors in pitch estimation. For this reason, scholars using median or mean vocal pitch should be able to estimate models that are quite robust to the selection of *Praat* floor and ceiling parameters. As a demonstration of this, we now turn to a replication of our results using floor and ceiling parameters that are outside the bounds of those recommended by either the literature or *Praat* software itself.

To demonstrate the robustness of summary statistics such as mean vocal pitch to the bounds set in *Praat*, we re-estimated our main results using arbitrary pitch floor and ceiling settings. We selected pitch floor values of 50, 75, and 100Hz, and pitch ceiling values of 300, 350, 400, 450, 550, and 600Hz for this analysis. Recall that the default *Praat* settings are 50Hz and 600Hz for the floor and ceiling respectively. We are thus significantly shrinking the pitch window used by *Praat* to demonstrate that summary statistics such as mean vocal pitch generate reliable findings even with arbitrarily smaller pitch windows. The replicated results for Table 1, Model 3 (from the main text) are shown in Figure S7. In this figure, each panel plots the coefficient estimates derived using different pitch floor and ceiling settings. The panels represent pitch floors of 50Hz, 75Hz, and 100Hz from left to right. Variations

Table S8: The Effect of Quantity and Intensity of Women's Speech on Men's Vocal Pitch (Different Pitch Windows)

	Dependent variable:		
	Male Vocal Pitch		
	Praat Default Settings	*Literature Suggested Settings*	*Praat Suggested Settings*
	(1)	(2)	(3)
Fixed Effects			
Constant	-0.019^{***}	-0.022^{***}	-0.028^{***}
	(0.007)	(0.007)	(0.007)
"Women" Mentioned	0.010	0.026	0.013
	(0.022)	(0.022)	(0.022)
Female Speeches	0.003^{***}	0.003^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)
Female Pitch	0.046^{***}	0.077^{***}	0.097^{***}
	(0.009)	(0.009)	(0.009)
"Women" Mentioned × Female Speeches	−0.003	−0.003	−0.004
	(0.003)	(0.003)	(0.003)
"Women" Mentioned × Female Pitch	0.029	0.004	−0.009
	(0.031)	(0.031)	(0.031)
Female Speeches × Female Pitch	0.012^{***}	0.012^{***}	0.008^{***}
	(0.002)	(0.002)	(0.002)
"Women" Mentioned × Female Speeches × Female Pitch	0.015^{***}	0.016^{***}	0.018^{***}
	(0.005)	(0.005)	(0.006)
Random Effects			
MC	0.000	0.000	0.000
N_1	49,919	49,914	49,962
N_2	506	506	506
Log Likelihood	−70,715.350	−70,478.580	−70,726.420
AIC	141,450.700	140,977.200	141,472.800

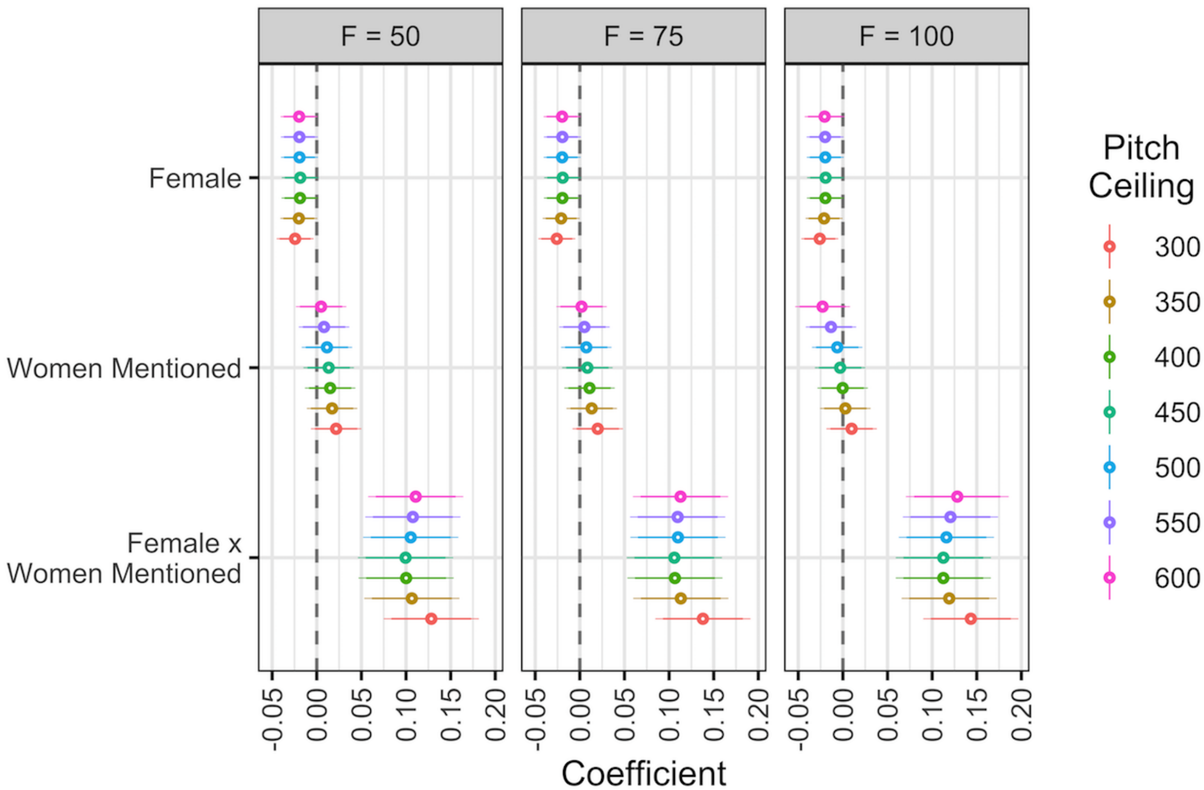
Note: The dependent variable is the speaker's vocal pitch in standard deviations above or below the speaker's baseline. In Model 1 the pitch floor and ceiling are set to 75Hz and 600Hz. In Model 2 the pitch floor and ceiling are set to 50Hz and 600Hz. In Model 3 the pitch floor and ceiling are set to 75Hz and 300Hz. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

Table S9: Effect of Quantity and Intensity of Women's Speech on Men's Voting Patterns (Different Pitch Windows)

	Dependent variable: Male Votes Cast					
	Praat Default Settings		*Literature Suggested Settings*		*Praat Suggested Settings*	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	0.020	0.100**	0.019	0.100**	0.018	0.095*
	(0.015)	(0.051)	(0.015)	(0.051)	(0.015)	(0.051)
Female Speeches	0.001	−0.00002	0.001	0.0001	0.001	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female Pitch	−0.189***	−0.179***	−0.187***	−0.177***	−0.179***	−0.167***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Female Speeches × Female Pitch	0.015***	0.012***	0.015***	0.012***	0.014***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls		✓		✓		✓
N_1	21,920	21,920	21,920	21,920	21,920	21,920
N_2	485	485	485	485	485	485
Log Likelihood	−28,118.740	−28,102.000	−28,122.730	−28,105.190	−28,128.860	−28,112.830
AIC	56,249.470	56,234.010	56,257.460	56,240.370	56,269.720	56,255.660

Note: Models are identical to Table 7, Models 1 and 2 except we use different Pratt settings. Control variables excluded to save space. Full models available upon request. Outcome is the proportion of time male MCs voted with women, as described on pages S36–S41. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

Figure S7: Female MCs More Likely to Talk About Women, with Greater Intensity (No Controls)



Note: Replicating the results from Table 1 (main text), Model 3 using a variety of *Praat* pitch floor and ceiling settings. More specifically, in the panels labeled "F = 50," "F = 75," and "F = 100," the pitch floor is set to 50Hz, 75Hz, and 100Hz, respectively. The colored points indicate the pitch ceiling which ranges from 300Hz (red) to 600Hz (magenta). On the x and y axises we show the coefficients and the variable labels, respectively. Thinner lines represent 95% confidence intervals. Thicker lines represent 90% confidence intervals. The vertical dashed line represents zero, meaning any interval that overlaps this line is statistically indistinguishable from zero.

in pitch ceiling are indicated by different colored circles within each panel. As you can see, the coefficient estimates vary only slightly across arbitrarily set pitch settings. Even with extreme *Praat* settings (i.e., a pitch floor of 100Hz and a ceiling of 300Hz), the substantive interpretation of results is essentially unchanged from our initial analysis, with the coefficient for our interaction term remaining positive, statistically significant, and substantively nearly identical to what we report in the main text.

Our coefficient estimates are similarly robust after the inclusion of additional control variables. Figure S8 replicates Table 1, Model 4 from the main text using a variety of pitch windows. As before, not only does the substantive interpretation of results remain unchanged with arbitrarily defined pitch windows, but the coefficient estimates themselves are virtually identical. This is likely due to the law of large numbers. Each point on the pitch contour is being drawn from the same distribution (the speaker's vocal range), meaning with a large enough sample the center of that distribution (the speaker's fundamental frequency) can be estimated using the sample mean (the speaker's mean vocal pitch). In *Praat*, the pitch floor and ceiling are important because they affect the sample size, but even when the pitch window is restrictive there will still be hundreds of pitch samples, which is likely enough to estimate the speaker's average fundamental frequency. Future work should be done to explore the bounds of sample size and pitch windows necessary to achieve robust results, but these results suggests that scholars should have a high degree of confidence in the use of mean vocal pitch with the *Praat* software, at least with sufficiently large data sets.

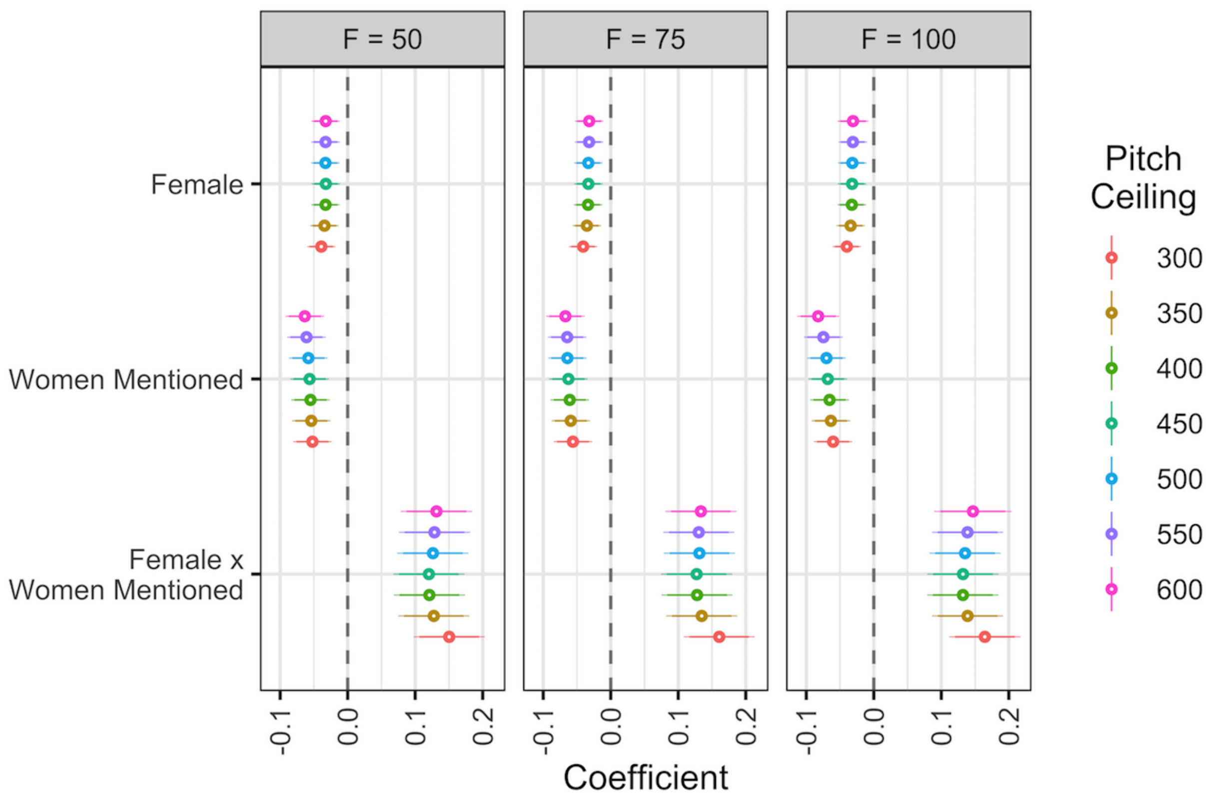
S5 Measuring Legislative Speech About Women

In addition to concerns about software choices and the estimation of mean pitch, one might be concerned about the sensitivity of our results to how we define speeches about women. We see at least three possible strategies for identifying legislative speech about women. The first, which we employ in the main text, is to identify whether a speech included any of the Pearson and Dancey (2011*b*) dictionary terms. If a speech used any of the terms in this dictionary, it was coded as a 1, otherwise it was coded as a 0. This is an established measure in the literature, so we are confident of its utility.

A second measure could consider the proportion of words in the speech drawn from dictionary terms. This measure would capture the degree to which the speech was referencing women, while also controlling for the fact that these references are more likely in longer speeches (thus eliminating the possibility that we are simply capturing speech length). We examine whether our results are robust to this alternative operationalization of the dependent variable (see discussion and Tables S11, S12, and S13 below).

Third, a more empirically-derived measure could be constructed from the floor speech texts themselves. Namely, one could use a Structural Topic Model (STM) (Roberts et al. 2013; Roberts, Stewart and Tingley 2014; Roberts et al. 2014) to capture speeches about women. This approach does not rely on a dictionary, which previous scholars have shown

Figure S8: Female MCs More Likely to Talk About Women, with Greater Intensity (with Controls)



Note: Replicating the results from Table 1 (main text), Model 4 using a variety of *Praat* pitch floor and ceiling settings. More specifically, in the panels labeled "F = 50," "F = 75," and "F = 100," the pitch floor is set to 50Hz, 75Hz, and 100Hz, respectively. The colored points indicate the pitch ceiling which ranges from 300Hz (red) to 600Hz (magenta). On the x and y axises we show the coefficients and the variable labels, respectively. Thinner lines represent 95% confidence intervals. Thicker lines represent 90% confidence intervals. The vertical dashed line represents zero, meaning any interval that overlaps this line is statistically indistinguishable from zero.

to be unreliable under certain conditions (Grimmer and Stewart 2013). Unlike standard Latent Dirichlet Allocation (LDA) models, STM allows researchers to use their substantive knowledge of the corpus to better "structure" topic identification (for additional details, see Roberts et al. 2014, 4). In the section below, we include two covariates in our structural topic model: the date of the speech and the speaker's ideology.

We assume that each legislative day is restricted to a handful of topics, meaning that representatives are likely to deliver similar speeches on the same day. Words appearing on the same day are thus more likely to be associated with one another. This variable was measured in days since the first date in the data set – January 1, 2009. We also assume that representatives who are on the same side of the ideological spectrum are more likely to speak about similar issues. We measure ideology using DW-Nominate scores which range from -1 ("liberal") to 1 ("conservative") (Poole and Rosenthal 2001). Using these covariates, we estimated a 30-topic STM, the results of which can be found in Table S15. We choose to focus on Topic 14, as it appears to be the most directly comparable to the set of terms chosen by Pearson and Dancey (2011*b*). More specifically, this topic includes word stems like "women," "children," "famili," "live," "life," and "children" which are all consistent with references to women.

S5.1 Replicating Results Using Different "Women" Operationalizations

Table S10 shows the comparability of each strategy for identifying speeches about women. The first column defines speeches about women by whether they included any of the Pearson and Dancey (2011*b*) terms. The second and third columns use the proportion of words in the speech that included these terms and whether the speech was classified under Topic 14 of our STM, respectively. As shown below, each of these measures yield substantively identical results. Not only are all the coefficients related to the speaker's gender (see `Female`) positive, but they are all highly significant. This suggests that irrespective of how we measure speech about women, female MCs are more likely to reference women on the House floor.

The results concerning women's vocal pitch are also consistent across the three measures. Table S11 reports these results. Here, the dependent variable is the standardized vocal pitch with positive values indicating MCs are speaking above their baseline. Our primary variable of interest is the interaction between a speaker's gender and whether the speaker mentions women. Again, in these models, the results are the same regardless of how the variable of interest is measured. This provides us with added confidence about the robustness of the findings we report in the main text concerning female legislators' increased amount and emotional intensity of speech referencing women.

To demonstrate the robustness of our findings about the responses of male legislators, we replicate our analyses using these alternative measures of speech about women. Our dependent variables in Table S12 capture whether a male MC referenced women in his speech using the same three definitions described above. In these models, our primary

Table S10: Number of Speeches About Women Across Different Dependent Variables

	Dependent variable:					
	"Women" Mentioned		"Women" Percent		"Women" Topic	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	−2.427***	−2.218***	0.050***	0.083***	2.446***	2.837***
	(0.035)	(0.184)	(0.003)	(0.017)	(0.072)	(0.366)
Female	0.866***	0.790***	0.126***	0.115***	2.310***	2.051***
	(0.078)	(0.081)	(0.008)	(0.008)	(0.172)	(0.173)
Controls		✓		✓		✓
N_1	74,151	74,151	74,151	74,151	74,150	74,150
N_2	619	619	619	619	619	619
Log Likelihood	−23,909.700	−22,786.800	−18,098.780	−18,101.540	−234,275.800	−234,221.500
AIC	47,825.410	45,595.610	36,205.570	36,227.090	468,559.700	468,466.900

Note: Models are identical to Table 1, Models 1 and 2 except we use different operationalizations of references to women (description on page S32). Control variables excluded to save space. Full models available upon request. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Table S11: Vocal Pitch of Speeches about Women Across Different Independent Variables

	Independent variable:					
	"Women" Mentioned		"Women" Percent		"Women" Topic	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	−0.002	0.151***	−0.001	0.143***	0.015***	0.172***
	(0.004)	(0.024)	(0.004)	(0.024)	(0.005)	(0.024)
Female	−0.017	−0.032***	−0.011	−0.027***	−0.006	−0.022**
	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Talking About "Women"	0.020	−0.054***	0.021	0.011	−0.007***	−0.008***
	(0.014)	(0.014)	(0.018)	(0.018)	(0.001)	(0.001)
Female × Talking About "Women"	0.090***	0.112***	0.051**	0.058**	0.005***	0.004***
	(0.027)	(0.027)	(0.024)	(0.024)	(0.001)	(0.001)
Controls		✓		✓		✓
N_1	71,198	71,198	71,198	71,198	71,197	71,197
N_2	613	613	613	613	613	613
Log Likelihood	−100,720.100	−99,645.100	−100,721.800	−99,645.990	−100,700.700	−99,606.080
AIC	201,452.100	199,318.200	201,455.600	199,320.000	201,413.300	199,240.200

Note: Models are identical to Table 1, Models 3 and 4 except we use different operationalizations of references to women (description on page S32). Control variables excluded to save space. Full models available upon request. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Table S12: The Effect of Quantity and Intensity of Women's Speech on Frequency of Men's Speeches on Women Across Different Dependent Variables

	Dependent variable:					
	"Women" Mentioned		"Women" Percent		"Women" Topic	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	-2.695^{***}	-2.237^{***}	0.021^{***}	0.061^{***}	1.997^{***}	2.642^{***}
	(0.041)	(0.220)	(0.002)	(0.013)	(0.069)	(0.365)
Female Speeches	0.056^{***}	0.060^{***}	0.006^{***}	0.006^{***}	0.109^{***}	0.108^{***}
	(0.003)	(0.003)	(0.0003)	(0.0003)	(0.006)	(0.006)
Female Pitch	-0.124^{***}	-0.129^{***}	-0.007^{***}	-0.008^{***}	-0.387^{***}	-0.360^{***}
	(0.031)	(0.032)	(0.002)	(0.002)	(0.046)	(0.046)
Female Speeches ×	0.009	0.011^{**}	0.002^{***}	0.002^{***}	0.022^{**}	0.016
Female Pitch	(0.005)	(0.006)	(0.0004)	(0.0004)	(0.010)	(0.010)
Controls		✓		✓		✓
N_1	50,235	50,235	50,235	50,235	50,234	50,234
N_2	509	509	509	509	509	509
Log Likelihood	−14,735.510	−13,950.230	2,065.148	2,044.574	−154,044.400	−153,962.700
AIC	29,481.010	27,930.460	−4,118.297	−4,057.148	308,100.800	307,957.400

Note: Models are identical to Table 5, Models 1 and 2 except we use different operationalizations of references to women (description on page S32). Control variables excluded to save space. Full models available upon request. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

independent variable is the interaction between `Female Speeches` and `Female Pitch`. This interaction effect captures the total number of speeches (`Female Speeches`) and the average vocal pitch for female MCs (`Female Pitch`) on a given legislative day. Moving from left to right, our results hold regardless of the measure of speech about women. This demonstrates the robustness of our finding that men talk about women more often when female legislators give more, and more intense, speeches about women.

Our finding that men's vocal pitch increases when talking about women in response to female MCs' quantity and intensity of speech also holds across measures, as shown in Table S13. Here, we predict the standardized vocal pitch for male MCs using the interaction between `Female Speeches`, `Female Pitch`, and whether the speaker references "women" (`Talking About Women`). As explained in the main text, these models determine whether the vocal pitch of a male MC changes with differences in female speaking behavior. As before, the results are substantively identical regardless of the measure of speeches about women we employ.

Finally, in Table S14 we replicate our results while also including controls for party identification, ideology, seniority, committee position, race, whether the speech was given in an election year, women's issue bills, and the number of CQ bills on a given legislative

Table S13: The Effect of Quantity and Intensity of Women's Speech on Men's Vocal Pitch Across Different Independent Variables

	Independent variable:		
	"Women" Mentioned	"Women" Percent	"Women" Topic
	(1)	(2)	(3)
Fixed Effects			
Constant	−0.022***	−0.017**	−0.008
	(0.007)	(0.007)	(0.007)
Talking About "Women"	0.026	−0.052*	−0.007***
	(0.022)	(0.029)	(0.001)
Female Speeches	0.003***	0.002**	0.004***
	(0.001)	(0.001)	(0.001)
Female Pitch	0.077***	0.069***	0.065***
	(0.009)	(0.009)	(0.010)
Talking About "Women" × Female Speeches	−0.003	0.009***	0.0001
	(0.003)	(0.003)	(0.0001)
Talking About "Women" × Female Speeches	0.004	0.148***	0.003*
	(0.031)	(0.046)	(0.002)
Female Speeches × Female Pitch	0.012***	0.015***	0.015***
	(0.002)	(0.002)	(0.002)
Talking About "Women" × Female Speeches × Female Pitch	0.016***	−0.011**	−0.0003
	(0.005)	(0.006)	(0.0003)
Random Effects			
MC	0.000	0.000	0.000
N_1	49,914	49,914	49,913
N_2	506	506	506
Log Likelihood	−70,478.580	−70,477.020	−70,468.530
AIC	140,977.200	140,974.000	140,957.100

Note: Outcome is the vocal pitch of male speakers scaled to standard deviations above their baseline. Column labels (e.g., "Women Mentioned") indicate how `Talking About ''Women''` was measured. Please refer to page S32 for descriptions of the different measures. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

day. Excepting a few minor differences, the interpretation of our results remain unchanged. Given that our findings are robust across three different dependent variables and hold with the inclusion of a number of control variables, we are confident that our measurement choice on women's speeches had little substantive effect on the results we report in the main text.

S5.2 Party Topics

In the main text we examine whether Democratic and Republican MCs speak with heightened pitch on issues traditionally owned by their respective parties. To conduct the analyses found in Table 4 in the main text – and Table S5 in the Supplemental Information – we had to identify issues that were owned by Democrats and Republicans. These are presented in Table S15. "Democratic issues" fell into three general categories: (1) social welfare, (2) land management/transportation, and (3) civil rights. These includes topic numbers 1, 2, 6, 13, 19, 22, 25, 28, and 29. For Republicans, we identified (1) defense, (2) immigration, and (3) tax/budget policy as "Republican issues." These include topic numbers 5, 8, 9, 10, 12, 15, 23, 26, and 30. Although there is no universally-accepted definition of which issues are owned by the Democratic and Republican parties, we feel that these selections are in keeping with general perceptions of the parties' issue ownership. Moreover, as we report in the main text, Democrats and Republicans dedicate a larger proportion of their speeches to topics owned by their parties ($t = 23.32, df = 74148, p < 0.001$ and $t = 30.46, df = 74148, p < 0.001$, respectively).

S6 Measuring Potential Backlash Effects

Below we discuss the standardized and unstandardized vote measures used to estimate the relationship between women's speech and men's voting behavior.

S6.1 Standardized Vote Measure

To determine whether male MCs were generally responding positively or negatively to women's speaking behavior, we created a measure which captures whether a given male MC votes with female speakers more than we would expect on the average legislative day. This is the variable we report in Table 7 of the main text.

For the purpose of illustration, we walk through the construction of this variable for a single, hypothetical legislative day (e.g., January 20, 2010). We refer to this as the "day of interest." To do so, we take the following steps:

1. Find women who gave speeches using any of the Pearson and Dancey (2011*b*) terms on the day of interest. Let's assume there are two women who gave such speeches: F1 and F2.

Table S14: The Effect of Quantity and Intensity of Women's Speech on Men's Vocal Pitch Across Different Independent Variables (with Additional Controls)

	Independent variable:		
	"Women" Mentioned	"Women" Percent	"Women" Topic
	(1)	(2)	(3)
Fixed Effects			
Constant	0.108***	0.109***	0.127***
	(0.030)	(0.030)	(0.030)
Talking About "Women"	−0.042*	−0.056**	−0.008***
	(0.022)	(0.028)	(0.001)
Female Speeches	0.003***	0.002*	0.003***
	(0.001)	(0.001)	(0.001)
Female Pitch	0.079***	0.072***	0.066***
	(0.009)	(0.009)	(0.010)
Talking About "Women" × Female Speeches	−0.003	0.009***	0.0001
	(0.003)	(0.003)	(0.0001)
Talking About "Women" × Female Pitch	−0.0003	0.134***	0.003*
	(0.030)	(0.045)	(0.002)
Female Speeches × Female Pitch	0.010***	0.013***	0.014***
	(0.002)	(0.002)	(0.002)
Talking About "Women" × Female Speeches × Female Pitch	0.016***	−0.011*	−0.0003
	(0.005)	(0.006)	(0.0002)
Controls	✓	✓	✓
N_1	49,914	49,914	49,913
N_2	506	506	506
Log Likelihood	−69,839.170	−69,843.180	−69,823.470
AIC	139,718.300	139,726.400	139,686.900

Note: Replicates results from Table 6 from the main text and Table S13 from the SI with the same battery of controls we have included in other models. Controls not shown to save space. Full models available upon request. Please refer to page S32 for descriptions of the different measures. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table S15: Democratic and Republican Issues Identified by the Structural Topic Model (STM) Outlined in Section S5

Topic	Word 1	Word 2	Word 3	Word 4	Word 5	Label	Proportion
1	court	case	justic	judg	law	law 1	0.01
2	right	peopl	constitut	american	freedom	rights	0.03
3	colleagu	support	today	like	new	collegiality 1	0.05
4	work	make	need	peopl	can	values	0.07
5	war	militari	afghanistan	forc	defens	middle east 1	0.02
6	school	educ	student	colleg	communiti	education	0.02
7	republican	american	democrat	will	pass	party	0.04
8	busi	small	regul	cost	will	business	0.02
9	budget	spend	cut	year	debt	spending cut	0.04
10	secur	nation	inform	protect	agenc	security	0.03
11	energi	oil	gas	will	price	energy	0.02
12	state	unit	texa	border	come	immigration 2	0.02
13	care	health	insur	will	cost	health care	0.04
14	women	children	famili	live	life	children	0.03
15	nuclear	israel	iran	world	peac	middle east 2	0.02
16	job	economi	creat	american	econom	jobs	0.04
17	peopl	get	thing	talk	got	discursive 1	0.05
18	honor	year	great	serv	first	collegiality 2	0.04
19	transport	build	new	system	air	transportation	0.02
20	financi	credit	loan	bank	street	financial	0.02
21	will	side	pass	floor	debat	procedural	0.05
22	water	land	area	communiti	nation	land	0.03
23	law	immigr	enforc	victim	crime	immigration	0.02
24	say	think	know	want	one	discursive 2	0.08
25	fund	program	million	provid	billion	welfare 1	0.04
26	tax	govern	pay	feder	american	tax	0.03
27	administr	quot	report	obama	public	administration	0.03
28	act	requir	author	law	provis	law 2	0.05
29	famili	food	benefit	million	cut	welfare 2	0.02
30	servic	veteran	nation	serv	support	veterans	0.03

Note: Blue and Red topics were flagged as Democratic and Republican issues, respectively. Top-5 words and labels from the ($k = 30$) STM outlined in Section S5 also included. The labels are not returned by the software. They were added after reviewing the top-5 words and other related output.

2. Find men who also gave speeches on the day of interest. Let's assume there are two men who gave such speeches: M1 and M2.

3. Using all the votes from the appropriate Congress, determine how often each male and female pair voted in the same direction. Convert this to a mean and standard deviation for the average legislative day.

To continue this example, let's assume the mean and standard deviation (see Step 3) for every male/female dyad was the following:

$\mu_{\texttt{M1,F1}} = .90$, $\sigma_{\texttt{M1,F1}} = .10$

$\mu_{\texttt{M1,F2}} = .80$, $\sigma_{\texttt{M1,F2}} = .10$

$\mu_{\texttt{M2,F1}} = .90$, $\sigma_{\texttt{M2,F1}} = .20$

$\mu_{\texttt{M2,F2}} = .80$, $\sigma_{\texttt{M2,F2}} = .10$

Thus, on the average legislative day `M1` and `F1` are likely to vote in the same direction 90 percent of the time with a standard deviation of 10 percent. This was calculated by subsetting the vote data using each legislative day in the appropriate Congress. In this example, January 20, 2010 is in the 111th Congress, so we would cycle through each day in the 111th Congress and calculate the percentage of time `M1` and `F1` voted together. Once done, we then take the mean and standard deviation across all the days, giving us an expectation of how often `M1` and `F1` should vote together on the average legislative day. We call this the "dyadic mean and standard deviation."

For the purposes of the example, let us assume there were only three days in the 111^{th} Congress. On these days, `M1` and `F1` voted in the following way:

$p1_{\texttt{M1,F1}} = .90$ (Day 1)

$p2_{\texttt{M1,F1}} = .80$ (Day 2)

$p3_{\texttt{M1,F1}} = 1$ (Day 3)

Thus, on Day 1 `M1` voted in the same direction as `F1` 90 percent of the time. On Day 2, `M1` voted in the same direction as `F1` 80 percent of the time. On Day 3, `M1` voted in the same direction as `F1` 100 percent of the time. If we took the mean and standard deviation of these values, we would get .90 and .10, respectively.

With these baseline measures in hand, we will now add the following step:

4. Find all the votes that occurred on the day of interest and determine the degree to which the male and female speakers cast votes in the same direction. Again, we restrict the female speakers to only those who delivered speeches using any of the Pearson and Dancey (2011*b*) terms.

For example, assume there were only two votes, `V1` and `V2`. To make things easier, we will report the votes associated with each dyad. These can be found here:

`M1` = `Yes`, `F1` = `Yes` (Vote 1)

`M1` = `Yes`, `F2` = `No` (Vote 1)

`M2` = `Yes`, `F1` = `Yes` (Vote 1)

`M2` = `Yes`, `F2` = `Yes` (Vote 1)

`M1` = `Yes`, `F1` = `Yes` (Vote 2)

`M1` = `Yes`, `F2` = `Yes` (Vote 2)

`M2` = `Yes`, `F1` = `Yes` (Vote 2)

`M2` = `Yes`, `F1` = `Yes` (Vote 2)

We can see that `M1` votes with `F1` 100 percent of the time, whereas he votes with `F2` 50 percent of the time. Conversely, `M2` votes with both `F1` and `F2` 100 percent of the time.

These percents are then standardized using the baseline measures calculated in Step 3. This yields the next step:

5. Standardize the percentage of instances male and female speakers vote in the same direction using the corresponding dyadic means and standard deviations. Again, restricting the female speakers to those who used at least one of the Pearson and Dancey (2011*b*) terms.

For example, when this is done for all the male (`M1` and `M2`) and female (`F1` and `F2`) speakers, we get the following:

`M1`, `F1` $= \frac{1-.90}{.10} = 1$

`M1`, `F2` $= \frac{.50-.80}{.10} = -3$

`M2`, `F1` $= \frac{1-.90}{.20} = 0.50$

`M2`, `F2` $= \frac{1-.80}{.10} = 2$

Finally, to convert these standardized percentages to an overall score for each male speaker, we simply take the average. This yields the final step:

6. Take the average of the standardize percentages created in Step 5. This average represents a male speaker's willingness to vote with female speakers who reference women on the day of interest, accounting for his baseline willingness to vote with those same female speakers.

When this is done for the male ($\texttt{M1}$ and $\texttt{M2}$) speakers, we get the following:

$\texttt{M1} = \frac{1-3}{2} = -1$

$\texttt{M2} = \frac{2+.50}{2} = 1.25$

In Table 7, we used the average of the standardized scores as our dependent variable with two important caveats. First, we only used "yea" or "nay" votes. Excluding "present" votes and abstentions is standard practice in the literature, and we follow this norm for our study.

Second, as is standard practice in the literature, we only considered passage votes on House bills and resolutions. For these, we downloaded the roll call "Description" files from *Voteview*. The dependent variable in Table 7 only considers legislation that began with either "HR" or "HRES."

S6.2 Unstandardized Vote Measure

As a robustness check, we re-estimated the models in Table 7 using raw percentages. These results can be found in Table S16. Here, we restricted the analysis to male MCs who spoke on the same day as the female MCs who are used to generate the `Female Speeches` and `Female Pitch` variables. As shown in Table S16, the interaction between `Female Speeches` and `Female Pitch` is statistically significant and the coefficients are in the same direction as those found in Table 7. The same is true for the main effects.

We also estimated separate models for Democratic and Republican men with both our standardized and raw percentage measures. For both Democratic and Republican men, the interaction between `Female Speeches` and `Female Pitch` is positive and statistically significant in all models, irrespective of the measure used. The same can be said for the main effects.

Finally, it is important to note that we use these analyses mostly to rule out the possibility that men's increased attention to, and intensity in talking about, women is evidence of a backlash effect. Thus, the results outlined in Table 7 in the main text and Table S16 in the Supplemental Information should not be considered in isolation. Instead, they should be seen as preliminary evidence that the reaction of male MCs is likely a net positive for the advancement of women's interests in the House of Representatives. We hope this finding sparks future work on this topic.

S7 Comparing Democratic and Republican Members of Congress

Below we re-estimate the models from the main text while splitting the sample by partisanship.

Table S16: The Effect of Women's Speech Amount and Intensity on Men's Voting Patterns (Raw Percent)

	All		Democrats		Republicans	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	0.634***	0.786***	0.912***	0.873***	0.427***	0.787***
	(0.015)	(0.033)	(0.008)	(0.036)	(0.013)	(0.168)
Female Speeches	−0.004***	−0.003***	0.002***	0.002***	−0.010***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female Pitch	−0.040***	−0.035***	0.022***	0.028***	−0.093***	−0.087***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.009)
Female Speeches × Female Pitch	0.005***	0.004***	−0.001	−0.003***	0.010***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
N_1	11,943	11,943	5,314	5,314	6,629	6,629
N_2	482	482	215	215	267	267
Log Likelihood	−4,229.062	−3,823.784	529.471	551.688	−3,379.338	−3,286.319
AIC	8,470.125	7,677.567	−1,046.942	−1,073.377	6,770.677	6,602.639

Note: Models are identical to Table 7 except the outcome is the percentage of time male MCs voted with women. Controls are not shown to save space. Full models available upon request. Column labels indicate the subset of data used (all men, Democratic men, or Republican men respectively). Levels of significance are reported as follows: *p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01. Standard errors are reported in parentheses.

S7.1 Party Effects Among Female MCs

First, we re-estimated the results outlined in Table 1 in the main text separately for Democratic and Republican women. In Table S17, the dependent variable is whether a female MC used any one of the Pearson and Dancey (2011*b*) terms. In the first two columns, we replicated the results reported in Table 1, Models 1 and 2 from the main text. In the next two columns, we re-estimated these same models using only Democratic women. In the final two columns, we did the same for Republican women. Our results do not change as one moves from left to right, suggesting the results reported in Table 1 of the paper cannot be attributed to a single party (e.g., Democrats). Indeed, it seems both Democratic and Republican women are more likely to reference women as compared to their male counterparts. This is also consistent with the results outlined in Section S3.

Similar results are found for Table 1, Models 3 and 4. These models from the main text are re-estimated in Table S18. Here, the dependent variable is standardized vocal pitch. In the first two columns, we replicated the results reported in Table 1. In the next two columns, we re-estimated these same models using only Democratic women. In the final two columns, we did the same for Republican women. Unlike the previous table, the results vary by party. Indeed, while the interaction term is in the same direction, the effect seems to be more pronounced for Democratic women. To ensure that our main results are not being driven solely by the behavior of Democratic women, the results we report in Table 1 control

Table S17: Female MCs' References to Women, by Party

	Dependent variable: "Women" Mentioned					
	All		Democrats		Republicans	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	-2.427^{***}	-2.364^{***}	-2.322^{***}	-2.171^{***}	-2.519^{***}	-1.693^{***}
	(0.035)	(0.116)	(0.050)	(0.181)	(0.050)	(0.641)
Female	0.866^{***}	0.795^{***}	0.784^{***}	0.794^{***}	0.905^{***}	0.875^{***}
	(0.078)	(0.081)	(0.093)	(0.097)	(0.147)	(0.144)
Controls		✓		✓		✓
N_1	74,151	74,151	36,190	36,190	37,961	37,961
N_2	619	619	314	314	305	305
Log Likelihood	−23,909.700	−22,787.330	−12,713.380	−12,172.230	−11,192.220	−10,589.030
AIC	47,825.410	45,594.650	25,432.760	24,364.460	22,390.440	21,198.070

Note: Models are identical to Table 1, Models 1 and 2. However, we subset our data by party identification. Controls not shown to save space. Full models available upon request. Column labels indicate the subset of data used (all MCs, Democrats, or Republicans respectively). Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

for the party identification of the speaker, meaning the general relationship we discuss in the paper cannot solely be attributed to the differential party effect outlined in this table. To emphasize this point, we plotted predicted values for Table S18, Models 1, 3, and 5 in Figure S9.

When we compare across the three panels ("All", "Democrats", and "Republicans"), we see a consistent positive relationship between gender and vocal pitch. This relationship is strongest for Democratic women. Indeed, although female Republicans tend to speak at a higher vocal pitch when referencing women, the 95-percent confidence intervals overlap considerably. Of course, this finding could be influenced by the comparatively smaller number of women in the Republican caucus, thus making it harder to detect an effect. To ensure that our main results are not being driven solely by the behavior of Democratic women, the results we report in Table 1 control for the party identification of the speaker, meaning the general relationship we discuss in the paper cannot solely be attributed to the differential party effect outlined in this plot.

S7.2 Party Effects Among Male MCs

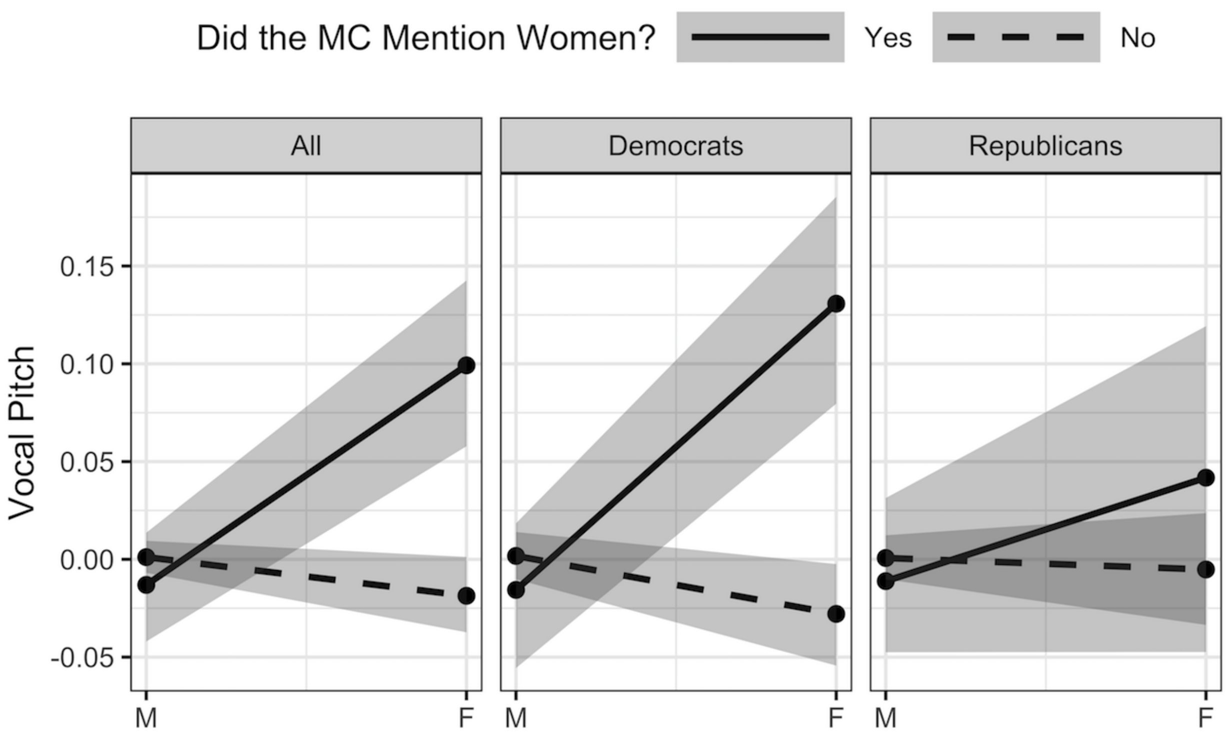
We also re-estimated Table 5 in the main text separating Democratic and Republican men (see Table S19). Tables S20 and S21 reports similar models for Tables 6 and 7. Although

Table S18: Female MCs' Standardized Vocal Pitch When Referencing Women, by Party

	Dependent variable: Standardized Vocal Pitch					
	All		Democrats		Republicans	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	−0.002	0.126***	−0.002	0.104***	−0.001	0.164
	(0.004)	(0.015)	(0.007)	(0.026)	(0.006)	(0.126)
Female	−0.017	−0.032***	−0.021	−0.033**	−0.008	−0.026
	(0.011)	(0.011)	(0.013)	(0.013)	(0.018)	(0.018)
"Women" Mentioned	0.020	−0.054***	0.024	−0.049**	0.017	−0.061***
	(0.014)	(0.014)	(0.021)	(0.021)	(0.020)	(0.020)
Female × "Women" Mentioned	0.090***	0.112***	0.101***	0.124***	0.051	0.065
	(0.027)	(0.027)	(0.034)	(0.034)	(0.049)	(0.049)
Controls		✓		✓		✓
N_1	71,198	71,198	34,837	34,837	36,361	36,361
N_2	612	612	310	310	302	302
Log Likelihood	−100,720.100	−99,643.370	−49,277.870	−48,791.520	−51,453.090	−50,878.630
AIC	201,452.100	199,312.700	98,567.740	97,609.050	102,918.200	101,783.300

Note: Models are identical to Table 1, Models 3 and 4. However, we subset our data by party identification. Controls not shown to save space. Full models available upon request. Column labels indicate the subset of data used (all men, Democratic men, or Republican men respectively). Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

Figure S9: Female MCs' Standardized Vocal Pitch When Referencing Women, by Party



Note: Predicted vocal pitch derived from Table 1, Model 2 in the main text. A dashed line indicates the speech mentioned "women." A solid line indicates all other speeches. In the x-axis we set the speaker's gender to either male or female. The y-axis has the predicted vocal pitch in standard deviations above or below the speakers' baseline. All other variables held constant.

Table S19: The Effect of Quantity and Intensity of Women's Speech on Quantity of Men's Speeches About Women, by Party

	Dependent variable: "Women" Mentioned					
	All		Democrats		Republicans	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	-2.695^{***}	-2.458^{***}	-2.650^{***}	-2.139^{***}	-2.735^{***}	-1.800^{**}
	(0.041)	(0.146)	(0.056)	(0.205)	(0.059)	(0.702)
Female Speeches	0.056^{***}	0.060^{***}	0.068^{***}	0.072^{***}	0.045^{***}	0.051^{***}
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)
Female Pitch	-0.124^{***}	-0.129^{***}	-0.109^{**}	-0.117^{**}	-0.131^{***}	-0.131^{***}
	(0.031)	(0.032)	(0.046)	(0.048)	(0.042)	(0.043)
Female Speeches × Female Pitch	0.009 (0.005)	0.011^{**} (0.006)	0.010 (0.008)	0.015^{*} (0.008)	0.005 (0.008)	0.006 (0.008)
Controls		✓		✓		✓
N_1	50,235	50,235	22,207	22,207	28,028	28,028
N_2	509	509	234	234	275	275
Log Likelihood	−14,735.510	−13,951.110	−6,782.614	−6,452.685	−7,936.107	−7,469.518
AIC	29,481.010	27,930.230	13,575.230	12,933.370	15,882.210	14,967.040

Note: Models are identical to Table 5, but we subset our data by party identification. Controls not shown to save space. Full models available upon request. Column labels indicate the subset of data used (all men, Democratic men, or Republican men respectively). Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

the results associated with Republican men seem to be more pronounced, when predicted values are plotted in Figure S10, we found very little difference across the parties. Indeed, the plots themselves are nearly identical.

The solid lines suggest Republican and Democratic men respond similarly to changes in female speaking behavior. Indeed, as both `Female Speeches` and `Female Pitch` increase, both Republican and Democratic men seem to become more emotionally activated when referencing women. These findings give us confidence that the results we present in the main text cannot be attributed to one party. Instead, male MCs from both parties increase their vocal pitch when a large number of female MCs deliver speeches on women with heightened vocal pitch.

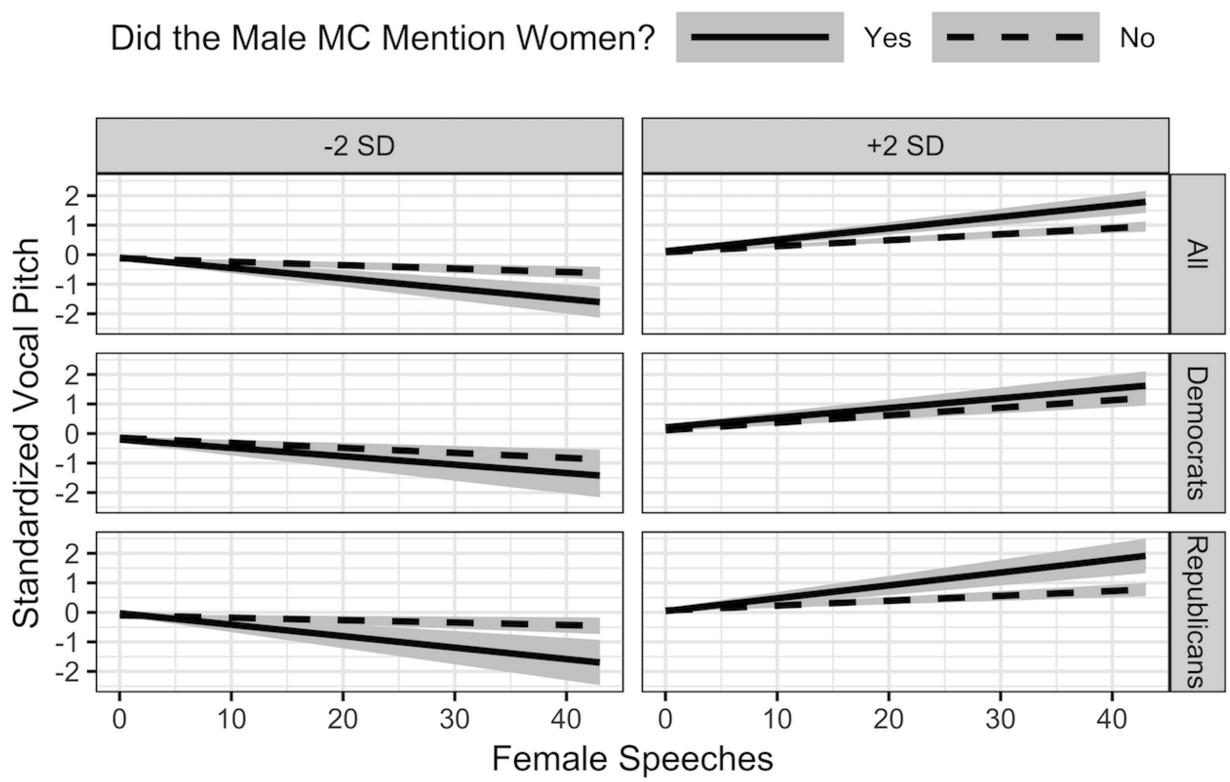
We also re-estimated the models in Table 7 from the main text using only Democratic or Republican men (see Table S21). Moving from left to right, it is readily apparent that our main results cannot be attributed to a single political party. Not only is the interaction between `Female Speeches` and `Female Pitch` positive and statistically significant, but the main effects of both variables are also the same in each model. To emphasize this point, we

Table S20: The Effect of Quantity and Intensity of Women's Speech on Men's Vocal Pitch by Party

	Dependent variable: Standardized Vocal Pitch		
	All	Democrats	Republicans
	(1)	(2)	(3)
Fixed Effects			
Constant	-0.022^{***}	-0.024^{**}	-0.021^{**}
	(0.007)	(0.010)	(0.009)
"Women" Mentioned	0.026	0.019	0.027
	(0.022)	(0.033)	(0.030)
Female Speeches	0.003^{***}	0.003^{*}	0.004^{**}
	(0.001)	(0.002)	(0.002)
Female Pitch	0.077^{***}	0.095^{***}	0.061^{***}
	(0.009)	(0.014)	(0.012)
"Women" Mentioned × Female Speeches	-0.003	-0.003	-0.003
	(0.003)	(0.004)	(0.004)
"Women" Mentioned × Female Pitch	0.004	0.058	-0.035
	(0.031)	(0.046)	(0.041)
Female Speeches × Female Pitch	0.012^{***}	0.016^{***}	0.009^{***}
	(0.002)	(0.003)	(0.003)
"Women" Mentioned × Female Speeches × Female Pitch	0.016^{***}	0.007	0.021^{***}
	(0.005)	(0.007)	(0.008)
Random Effects			
MC	0.000	0.000	0.000
N_1	49,914	22,080	27,834
N_2	506	233	273
Log Likelihood	$-70{,}478.580$	$-31{,}110.330$	$-39{,}385.840$
AIC	140,977.200	62,240.650	78,791.680

Note: Outcome is the vocal pitch of male speakers scaled to standard deviations above his baseline. `''Women'' Mentioned` indicates whether the speech used any of the Pearson and Dancey (2011*b*) terms. Column labels indicate the subset of data used (all men, Democratic men, or Republican men respectively). Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

Figure S10: Estimated Effect of Quantity and Intensity of Women's Speeches on Men's Emotional Intensity by Party



Note: Predicted male vocal pitch derived from Table 6, Model 1 in the main text. Solid lines indicate a speech using a Pearson and Dancey (2011*b*) term, dashed lines indicate all other speeches. The y-axis displays the standardized vocal pitch of male speeches. On the x-axis `Female Speeches` is allowed to vary from its minimum (0) to maximum (43). The left panel shows `Female Pitch` set to two standard deviations below the mean. The right panel shows `Female Pitch` set to two standard deviations above the mean. Gray ribbons represent 90% confidence intervals. 95% confidence intervals look very similar, but the wide range in predicted values makes it difficult to see differences.

Table S21: The Effect of Women's Speech Amount and Intensity on Men's Voting Patterns (Standardized Percent)

	Dependent variable: Male Votes Cast					
	All		Democrats		Republicans	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	0.019	0.100**	−0.026	0.127*	0.053**	0.503*
	(0.015)	(0.051)	(0.019)	(0.070)	(0.022)	(0.260)
Female Speeches	0.001	0.0001	0.011***	0.009***	−0.005***	−0.005***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Female Pitch	−0.187***	−0.177***	−0.221***	−0.205***	−0.120***	−0.126***
	(0.013)	(0.013)	(0.017)	(0.017)	(0.019)	(0.020)
Female Speeches × Female Pitch	0.015***	0.012***	0.012***	0.010***	0.013***	0.012***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Controls		✓		✓		✓
N_1	21,920	21,920	11,619	11,619	10,301	10,301
N_2	485	485	221	221	264	264
Log Likelihood	−28,122.730	−28,105.190	−15,270.430	−15,220.490	−12,800.010	−12,800.760
AIC	56,257.460	56,240.370	30,552.870	30,470.980	25,612.030	25,631.520

Note: Outcome is the percentage of time male MCs voted with women, as described on pages S36–S41. Control variables not shown to save space. Full models available upon request. Column labels indicate the subset of data used (all men, Democratic men, or Republican men respectively). Levels of significance are: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

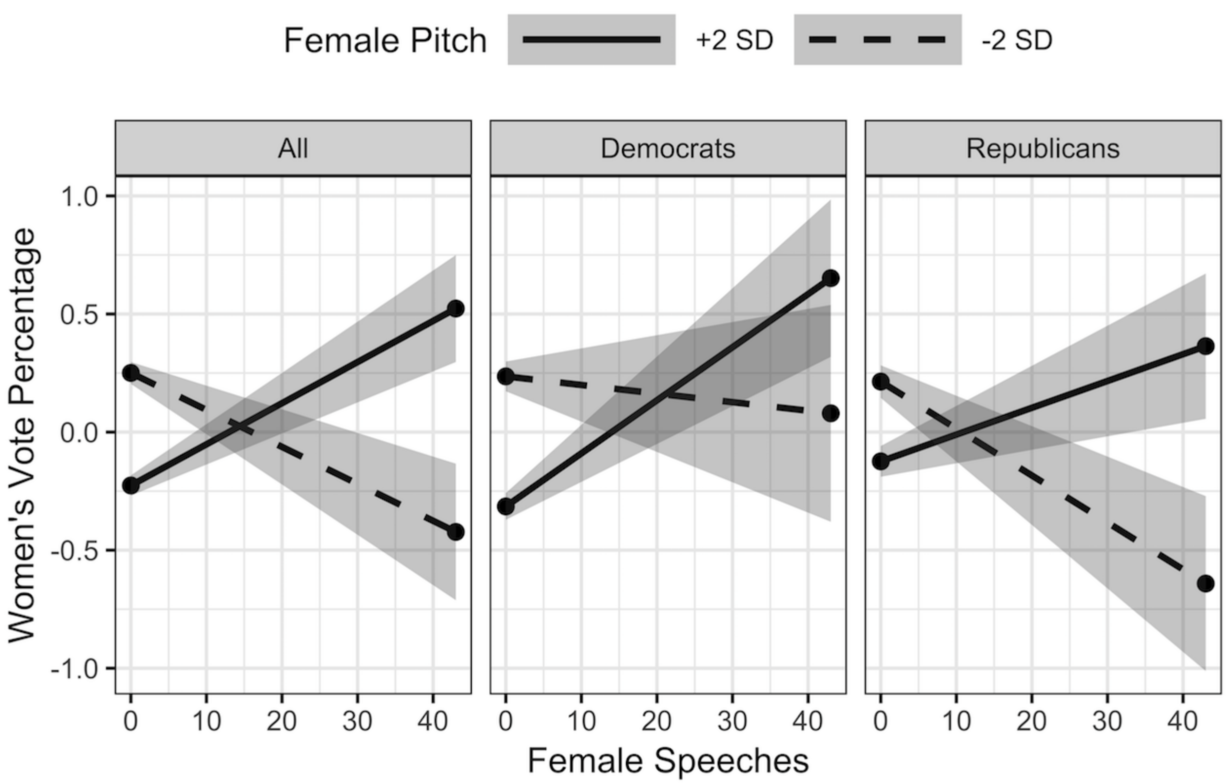
plotted predicted values for Table S21, Models 1, 3, and 5 in Figure S11.

In the first panel (see "All") we find a plot identical to Figure 3 in the main text. Here, we use the coefficients from Table S21, Model 1 to show male MCs tend to vote more with women as both `Female Speeches` and `Female Pitch` increase. In the second (see "Democrats") and third (see "Republicans") panels, we replicate the main result reported in Table 7 of the main text using only Democrats and Republicans. Not only is there generally a positive effect associated with increases in `Female Speeches` and `Female Pitch`, but the change is nearly identical for both groups. This suggests that men generally respond favorably to female speeches about women when they are delivered in large numbers and with a heightened vocal pitch.

S8 Alternative Model Specifications

Below we present a series of alternative model specifications.

Figure S11: Estimated Effect of Quantity and Intensity of Women's Speeches on Men's Voting Behavior by Party



Note: Predicted male voting behavior from Models 1 ("All"), 3 ("Democrats"), and 5 ("Republicans") in Tables S21. Solid and dashed lines indicate `Female Pitch` was set to two standard deviations above and below the mean respectively. On the x-axis `Female Speeches` is allowed to vary from its minimum (0) to maximum (43). The y-axis has the percentage of time the male MC voted with women, as described on pages S36–S41.

S8.1 Random Intercept: Speaker and Day

In the models we report in the main text, we view each speech as being a single observation that we can use to measure the emotional intensity a MC uses when speaking about women. Since we should expect multiple observations from the same MC to be related, we nest each speech within the MC. This not only accounts for potential speaker-level clustering, but is also consistent with our broader conceptualization of legislative speech.

One concern is that speeches are clustered not only at the legislator-level, but also at the day-level. In order to address the possibility that there is residual day-level clustering that we are not accounting for with the inclusion of controls for number of bills on women's interests and CQ bills, below we discuss several strategies for addressing day-level clustering.

The first possibility is to include a random intercept for each day. However, this is problematic due to the nature of legislative speech in the U.S. House. Many legislators give only a single speech on any given legislative day. Thus, we would be nesting both legislators and speeches within the same upper-level unit. This makes it nearly impossible for these models to converge, making this option methodologically intractable.

A second approach is to include a random intercept for each speaker-day pairing. This type of model would assume that MCs bring a certain level of emotional intensity towards discussing women on each legislative day. Similar to a repeated-measure design, this modeling strategy views each speech as being nested within each legislator, but unlike the modeling strategy used in the main text, this random intercept structure assumes that the level of emotional intensity in discussing women varies by day within each legislator.

We replicated the results reported in the main text using this modeling strategy of nesting speeches within each speaker-day. These results are reported in Tables S22-S25. Of these, Tables S22 and S23 are the most relevant. The former replicates Table 1, Models 1 and 2 including a random intercept for each speaker-day instead of a random intercept for each speaker. In each of these models women are found to speak significantly more about women, regardless of the measure one uses to operationalize references to women. The latter replicates Table 1, Models 3 and 4. Here too we find the results remain essentially unchanged. Most importantly, the interaction between `Female` and `Talking about ''Women''` is positive and statistically significant, suggesting that women tend to speak with more emotional intensity when talking about women.

Our findings concerning male MCs' responses are also consistent when using this alternative modeling strategy. In Table S24 we show that male MCs are more likely to talk about women when a large number of female speeches are delivered about women with emotional intensity, precisely what we reported in Table 5 in the main text. Somewhat more mixed results are found in Table S25, which uses men's vocal pitch as the dependent variable.

Model 1 replicates our findings from the main text, but the interaction terms in Models 2 and 3 are less consistent. We think this can be attributed in part to the complexity of the interaction term and the restrictiveness of the speaker-day random intercept. More

Table S22: Female MCs More Likely to Talk About Women (Speaker and Day)

	Dependent variable:					
	"Women" Mentioned		"Women" Percent		"Women" Topic	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	−8.525***	−5.192***	0.052***	0.108***	2.598***	3.806***
	(0.081)	(0.001)	(0.002)	(0.010)	(0.033)	(0.185)
Female	0.943***	0.523***	0.133***	0.122***	2.175***	1.922***
	(0.095)	(0.081)	(0.004)	(0.004)	(0.073)	(0.075)
Controls		✓		✓		✓
N_1	74,151	74,151	74,151	74,151	74,150	74,150
N_2	36,240	36,240	36,240	36,240	36,240	36,240
Log Likelihood	−21,943.300	−21,149.460	−15,882.600	−15,824.220	−232,303.700	−232,153.300
AIC	43,892.590	42,320.920	31,773.200	31,672.430	464,615.300	464,330.700

Note: Re-estimated models found in Table S10 including a random intercept for the speaker-day, rather than a random intercept for just the speaker. Controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Table S23: Female MCs More Likely to Talk About Women with Greater Emotional Intensity (Speaker and Day)

	Dependent variable:					
	"Women" Mentioned		"Women" Percent		"Women" Topic	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	0.056***	0.227***	0.059***	0.219***	0.075***	0.245***
	(0.005)	(0.030)	(0.005)	(0.030)	(0.006)	(0.030)
Female	−0.019	−0.033**	−0.011	−0.027**	−0.008	−0.021
	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)
Talking About "Women"	0.033**	−0.046***	0.014	0.006	−0.006***	−0.007***
	(0.014)	(0.014)	(0.018)	(0.017)	(0.001)	(0.001)
Female ×	0.088***	0.110***	0.055**	0.059**	0.005***	0.004***
Talking About "Women"	(0.027)	(0.026)	(0.024)	(0.024)	(0.001)	(0.001)
Controls		✓		✓		✓
N_1	71,198	71,198	71,198	71,198	71,197	71,197
N_2	36,240	36,240	36,240	36,240	36,240	36,240
Log Likelihood	−21,943.300	−21,149.460	−15,882.600	−15,824.220	−232,303.700	−232,153.300
AIC	−97,074.120	−95,799.470	−97,082.070	−95,801.030	−97,065.360	−95,771.050

Note: Re-estimated models found in Table S11 including a random intercept for the speaker-day, rather than a random intercept for just the speaker. Controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Table S24: The Effect of Quantity and Intensity of Women's Speech on Quantity of Men's Speeches About Women (Speaker and Day)

	Dependent variable:					
	"Women" Mentioned		"Women" Percent		"Women" Topic	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed Effects						
Constant	−8.559***	−4.564***	0.021***	0.072***	2.078***	3.012***
	(0.214)	(0.0002)	(0.002)	(0.009)	(0.048)	(0.217)
Female Speeches	0.068**	0.082***	0.007***	0.007***	0.126***	0.123***
	(0.029)	(0.0002)	(0.0003)	(0.0003)	(0.008)	(0.008)
Female Pitch	−0.130	−0.179***	−0.010***	−0.010***	−0.565***	−0.532***
	(0.292)	(0.0002)	(0.003)	(0.003)	(0.063)	(0.063)
Female Speeches × Female Pitch	0.010	0.028***	0.002***	0.002***	0.029**	0.026**
	(0.050)	(0.0002)	(0.001)	(0.001)	(0.013)	(0.013)
Controls		✓		✓		✓
N_1	50,235	50,235	50,235	50,235	50,234	50,234
N_2	23,413	23,413	23,413	23,413	23,413	23,413
Log Likelihood	−13,639.910	−13,243.050	2,649.738	2,662.739	−152,781.600	−152,668.600
AIC	27,289.830	26,516.100	−5,287.477	−5,293.478	305,575.200	305,369.200

Note: Re-estimated models found in Table S12 including a random intercept for the speaker-day, rather than a random intercept for just the speaker. Controls excluded to save space. Full models available upon request. All models converged, except for Models 1 and 2. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Table S25: The Effect of Quantity and Intensity of Women's Speech on Men's Vocal Pitch by Party (Speaker and Day)

	Independent variable:		
	"Women" Mentioned	"Women" Percent	"Women" Topic
	(1)	(2)	(3)
Constant	0.031***	0.038***	0.048***
	(0.009)	(0.008)	(0.009)
"Women" Mentioned	0.041*	−0.038	−0.006***
	(0.021)	(0.028)	(0.001)
Female Speeches	0.003**	0.002	0.003**
	(0.001)	(0.001)	(0.001)
Female Pitch	0.087***	0.081***	0.076***
	(0.012)	(0.011)	(0.012)
"Women" Mentioned × Female Speeches	−0.003	0.006**	0.0001
	(0.003)	(0.003)	(0.0001)
"Women" Mentioned × Female Pitch	0.018	0.124***	0.002
	(0.030)	(0.044)	(0.002)
Female Speeches × Female Pitch	0.012***	0.014***	0.015***
	(0.002)	(0.002)	(0.002)
"Women" Mentioned × Female Speeches × Female Pitch	0.012**	−0.007	−0.0003
	(0.005)	(0.006)	(0.0002)
N_1	49,914	49,914	49,913
N_2	23,323	23,323	23,323
Log Likelihood	−67,951.430	−67,951.580	−67,947.370
AIC	135,922.900	135,923.200	135,914.700

Note: Re-estimated models found in Table S13 including a random intercept for the speaker-day, rather than a random intercept for just the speaker. Outcome is the vocal pitch of male speakers scaled to standard deviations above their baseline. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

specifically, many legislators give only one speech on a given day. In these cases, the speaker-day random intercept is perfectly correlated with the day-level female speech and vocal pitch variables. Indeed, we cannot re-estimate the vote models we report in the main text (see Table 7) because in many cases the speaker-day random intercept was essentially identical to the dependent variable, which was a day-level measure of vote congruity. For these reasons, we believe that our original modeling strategy is more methodologically sound, even though we fully acknowledge that it does not perfectly address day-level clustering.

S8.2 Speaker Order: Dyadic Model

To address concerns about the temporal ordering of speeches when evaluating men's response to female MCs' speeches, we also estimated several dyadic models. By taking into account the temporal ordering of speeches, these models help us investigate whether there is an immediate backlash to an individual female MC's emotionally intense speech. Of course, since we are still relying on observational data, we are unable to test the causal mechanism linking female MCs' speeches to male MCs' subsequent behavior. At the same time, these models do allow us to have greater confidence in our findings concerning the absence of backlash effects.

In the first dyadic model specification, we simply see whether women speaking more about women at a higher vocal pitch can increase the likelihood that the next speaker (1) talks more about women, and (2) votes more with the preceding female speaker. That is, we examine the effect of the percent of the current speech which uses any of the Pearson and Dancey (2011*b*) terms (`"Women" Percent`$_t$) on the percent of the subsequent speech that uses any of the Pearson and Dancey (2011*b*) terms (`"Women" Percent`$_{t+1}$). In the second dyadic model specification, the dependent variables are the same, but we change the independent variable from whether the previous female speaker raises her vocal pitch above her baseline to whether the female speaker raised her pitch higher than the previous speaker. That is, we compare `Vocal Pitch`$_t$ to `Vocal Pitch`$_{t-1}$ to determine if that female MC's speech referencing women was more emotionally intense than the speech preceding it. In this way, we account for whether it is women's speeches that are elevating the emotional intensity of the chamber, or if both men's and women's speeches are responding to the broader emotional environment on the floor.

In Table S26, we present the results from our dyadic models. In Panel A, we report the standardized vocal pitch of the female MC (`Vocal Pitch`$_t$), whereas in Panel B we report the standardized vocal pitch of the female MC relative to the previous speech (`Vocal Pitch`$_t$ `-Vocal Pitch`$_{t-1}$). To account for likely clustering within dyads, we included a random intercept for each dyad. The results in Table S26 are consistent with Table 5 in the main text. In Panel A, when a female MC uses more Pearson and Dancey (2011*b*) terms (`"Women" Percent`$_t$) in a speech with greater emotional intensity (`Vocal Pitch`$_t$), a speech by a male MC given immediately after her speech will tend to include a greater percentage of words about women. This result holds when we introduce our control variables (Model 2). Panel

Table S26: The Effect of Quantity and Intensity of Women's Speech on Quantity of Men's Speeches About Women (Dyads #1)

(a) Vocal Pitch$_t$

	Dependent variable:	
	"Women" Percent$_{t+1}$	
	(1)	(2)
Constant	0.0002**	0.001***
	(0.0001)	(0.0005)
"Women" Percent$_t$	1.240***	1.240***
	(0.022)	(0.022)
Vocal Pitch$_t$	0.00003	0.0001
	(0.0001)	(0.0001)
$\lvert$Ideology$_{t+1}$ - Ideology$_t\rvert$		−0.0003
		(0.0002)
$\lvert$Duration$_{t+1}$ - Duration$_t\rvert$		0.0001***
		(0.00003)
Same Race		−0.00002
		(0.0003)
Same Chair		−0.001***
		(0.0003)
Election Year		0.0001
		(0.0002)
"Women" Percent$_t$ × Vocal Pitch$_t$	0.070***	0.071***
	(0.024)	(0.024)
N	6,807	6,807
Log Lik	22,344.870	22,316.340
AIC	−44,677.740	−44,610.680

(b) Vocal Pitch$_t$ -Vocal Pitch$_{t-1}$

	Dependent variable:	
	"Women" Percent$_{t+1}$	
	(3)	(4)
Constant	0.0002**	0.001***
	(0.0001)	(0.0005)
"Women" Percent$_t$	1.246***	1.247***
	(0.021)	(0.021)
Vocal Pitch$_t$ - Vocal Pitch$_{t-1}$	0.00004	0.0001
	(0.0001)	(0.0001)
$\lvert$Ideology$_{t+1}$ - Ideology$_t\rvert$		−0.0003
		(0.0002)
$\lvert$Duration$_{t+1}$ - Duration$_t\rvert$		0.0001***
		(0.00003)
Same Race		−0.00003
		(0.0003)
Same Chair		−0.001***
		(0.0003)
Election Year		0.0001
		(0.0002)
"Women" Percent$_t$ × (Vocal Pitch$_t$ - Vocal Pitch$_{t-1}$)	0.053***	0.053***
	(0.019)	(0.019)
N	6,802	6,802
Log Lik	22,325.240	22,296.620
AIC	−44,638.480	−44,571.250

Note: Results are from dyadic models in which a female MC (t) speaks before a male MC ($t+1$). In all models the dependent variable is the total number of times the male MC ($t+1$) used one of the Pearson and Dancey (2011*b*) terms divided by the total number of words in the speech (`"Women" Percent`$_{t+1}$). In Panel A, we interact the total number of times the female MC used one of the Pearson and Dancey (2011*b*) terms divided by the total number of words in the speech (`"Women" Percent`$_t$) with the female MC's standardized vocal pitch (`Vocal Pitch`$_t$). In Panel B, we interact `"Women" Percent`$_t$ with the female MC's standardized vocal pitch minus the standardize vocal pitch from the previous speaker `Vocal Pitch`$_{t-1}$. Ultimately, this variable (`Vocal Pitch`$_t$-`Vocal Pitch`$_{t-1}$) captures whether the female MC was more emotionally intense than the previous speaker. These models report the results from a multilevel linear regression. All models also include a randomly varying intercept for each dyad. Levels of significance are reported as follows: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

B shows evidence that male MCs' speeches are responding to changes in the vocal pitch of women's speeches, rather than the two rising in response to a previous speech. When a female MC uses more Pearson and Dancey (2011*b*) terms with a higher standardized vocal pitch than the speaker preceding her ($\texttt{Vocal Pitch}_t$ -$\texttt{Vocal Pitch}_{t-1}$), a subsequent speech by a male MC is likely to devote a higher percentage of the speech to talking about women. This evidence reinforces our findings in the main text. When female MCs talk more about women, and with greater intensity, male MCs become more likely to talk about women.

Table S27 addresses the much more difficult question of vote choice. As explained in the main text, it is difficult to imagine that a single female speech will influence male voting behavior. Instead, we argue that it is when a large number of female MCs take to the floor and give emotionally intense speeches about women that we should see men's voting patterns change. Moreover, unlike references to women, it is even more difficult to measure the effect of a single female speech on male voting behavior immediately after the female speech has concluded, since we cannot easily identify when votes occurred relative to speeches. With those caveats in mind, we now present a supplementary analysis using dyads to explore whether female MCs' speeches about women affect men's voting patterns. Instead of focusing on the degree to which a given male MC votes with all female speakers we are only going to consider the degree to which a male MC votes with the female speaker who directly preceded him. In our first set of analyses, we focus on the raw number of votes cast in the same direction. In our second set of analyses, we examine the percentage of votes cast in the same direction.

As before, we report the results of two models. The first, in Panel A, reports the effect of the standardized vocal pitch of the female MC ($\texttt{Vocal Pitch}_t$). The second, in Panel B, reports the standardized vocal pitch of the female MC relative to the previous speech ($\texttt{Vocal Pitch}_t$ -$\texttt{Vocal Pitch}_{t-1}$) to help isolate the effect of a single woman's speech. In both Panels, we see evidence that a female MC's emotionally intense speech about women has a positive effect on the likelihood that the subsequent male speaker votes in the same direction as her. The large and statistically significant interaction term, ``Women'' $\texttt{Percent}_t \times \texttt{Vocal Pitch}_t$, shows this effect. As the percent of Pearson and Dancey (2011*b*) terms and standardized vocal pitch in a female MC's speech increase, an immediately following male speaker is significantly more likely to vote with that female MC on that day. This result holds with the introduction of control variables (Model 2), as well as when we consider whether the female MC's standardized vocal pitch was higher than the speaker preceding her (Models 3 and 4). Although these results are insufficient for demonstrating a causal relationship, they are consistent with the argument that the content and emotional intensity of women's speeches are linked to men's behaviors in the U.S. House.

Table S28 replicates these results using the percentage of votes cast in the same direction instead of the total number of identical votes. We find less consistent evidence of an effect on voting behavior here. When using a female MC's standardized vocal pitch (Models 1 and 2), we find a positive but statistically insignificant interaction effect between vocal pitch and percent of terms related to women. When considering whether a female MC's standardized

Table S27: Effect of Quantity and Intensity of Women's Speech on Men's Voting Patterns (Dyads #2)

(a) Vocal Pitch_t

	Dependent variable:	
	Same Votes	
	(1)	(2)
Constant	2.248***	3.500***
	(0.030)	(0.101)
"Women" Percent_t	−10.754**	−8.411*
	(5.387)	(4.874)
Vocal Pitch_t	−0.111***	−0.061**
	(0.028)	(0.026)
$\lvert\text{Ideology}_{t+1}$ - $\text{Ideology}_t\rvert$		−1.690***
		(0.050)
$\lvert\text{Duration}_{t+1}$ - $\text{Duration}_t\rvert$		−0.002
		(0.006)
Same Race		0.001
		(0.062)
Same Chair		−0.135*
		(0.074)
Election Year		0.270***
		(0.049)
"Women" Percent_t × Vocal Pitch_t	13.833**	12.884**
	(5.909)	(5.331)
N	4,854	4,854
Log Lik	−9,887.093	−9,386.306
AIC	19,786.190	18,794.610

(b) Vocal Pitch_t -Vocal Pitch_{t-1}

	Dependent variable:	
	Same Votes	
	(3)	(4)
Constant	2.232***	3.500***
	(0.030)	(0.101)
"Women" Percent_t	−9.499*	−7.237
	(5.359)	(4.842)
Vocal Pitch_t - Vocal Pitch_{t-1}	−0.106***	−0.091***
	(0.021)	(0.019)
$\lvert\text{Ideology}_{t+1}$ - $\text{Ideology}_t\rvert$		−1.688***
		(0.050)
$\lvert\text{Duration}_{t+1}$ - $\text{Duration}_t\rvert$		−0.002
		(0.006)
Same Race		0.002
		(0.062)
Same Chair		−0.134*
		(0.074)
Election Year		0.285***
		(0.049)
"Women" Percent_t × (Vocal Pitch_t - Vocal Pitch_{t-1})	13.956***	13.914***
	(4.942)	(4.484)
N	4,851	4,854
Log Lik	−9,875.795	−9,370.803
AIC	19,763.590	18,763.610

Note: Results are from dyadic models in which a female MC (t) speaks before a male MC ($t+1$). In all models the dependent variable is the total number of times the male MC ($t+1$) cast the same vote as the female MC (t) on the day of the dyadic interaction. In Panel A, we interact the total number of times the female MC used one of the Pearson and Dancey (2011*b*) terms divided by the total number of words in the speech (`''Women'' Percent`$_t$) with the female MC's standardized vocal pitch (`Vocal Pitch`$_t$). In Panel B, we interact `''Women'' Percent`$_t$ with the female MC's standardized vocal pitch minus the standardize vocal pitch from the previous speaker `Vocal Pitch`$_{t-1}$. Ultimately, this variable (`Vocal Pitch`$_t$-`Vocal Pitch`$_{t-1}$) captures whether the female MC was more emotionally intense than the previous speaker. These models report the results from a multilevel linear regression. All models also include a randomly varying intercept for each dyad. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Table S28: Effect of Quantity and Intensity of Women's Speech on Men's Voting Patterns (Dyads #3)

(a) Vocal Pitch_t

	Dependent variable:	
	Same Percent	
	(1)	(2)
Constant	0.605***	0.988***
	(0.006)	(0.017)
"Women" Percent_t	−2.264**	−1.464*
	(0.990)	(0.797)
Vocal Pitch_t	−0.025***	−0.012***
	(0.005)	(0.004)
$\lvert\text{Ideology}_{t+1}$ - $\text{Ideology}_t\rvert$		−0.476***
		(0.008)
$\lvert\text{Duration}_{t+1}$ - $\text{Duration}_t\rvert$		0.001
		(0.001)
Same Race		−0.026**
		(0.010)
Same Chair		−0.019
		(0.012)
Election Year		−0.002
		(0.008)
"Women" Percent_t × Vocal Pitch_t	1.285	0.939
	(1.094)	(0.873)
N	4,854	4,854
Log Lik	−1,769.599	−617.486
AIC	3,551.198	1,256.972

(b) Vocal Pitch_t -Vocal Pitch_{t-1}

	Dependent variable:	
	Same Percent	
	(3)	(4)
Constant	0.602***	0.986***
	(0.006)	(0.017)
"Women" Percent_t	−2.201**	−1.451*
	(0.988)	(0.794)
Vocal Pitch_t - Vocal Pitch_{t-1}	−0.012***	−0.008**
	(0.004)	(0.003)
$\lvert\text{Ideology}_{t+1}$ - $\text{Ideology}_t\rvert$		−0.477***
		(0.008)
$\lvert\text{Duration}_{t+1}$ - $\text{Duration}_t\rvert$		0.001
		(0.001)
Same Race		−0.025**
		(0.010)
Same Chair		−0.019
		(0.012)
Election Year		−0.001
		(0.008)
"Women" Percent_t × (Vocal Pitch_t - Vocal Pitch_{t-1})	1.779**	1.505**
	(0.903)	(0.735)
N	4,851	4,854
Log Lik	−1,775.689	−617.998
AIC	3,563.377	1,257.997

Note: Results are from dyadic models in which a female MC (t) speaks before a male MC ($t+1$). In all models the dependent variable is the percent of time the male MC ($t+1$) cast the same vote as the female MC (t) on the same day as the dyadic interaction. In Panel A, we interact the total number of times the female MC used one of the Pearson and Dancey (2011*b*) terms divided by the total number of words in the speech (`''Women'' Percent`$_t$) with the female MC's standardized vocal pitch (`Vocal Pitch`$_t$). In Panel B, we interact `''Women'' Percent`$_t$ with the female MC's standardized vocal pitch minus the standardize vocal pitch from the previous speaker `Vocal Pitch`$_{t-1}$. Ultimately, this variable (`Vocal Pitch`$_t$-`Vocal Pitch`$_{t-1}$) captures whether the female MC was more emotionally intense than the previous speaker. These models report the results from a multilevel linear regression. All models also include a randomly varying intercept for each dyad. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Table S29: Effect of Quantity and Intensity of Women's Speech on Men's Voting Patterns (Placebo #1)

(a) Vocal Pitch$_t$

	Dependent variable:	
	Same Votes	Same Percent
	(1)	(2)
Constant	2.248***	0.605***
	(0.030)	(0.006)
"Women" Percent$_t$	−10.754**	−2.264**
	(5.387)	(0.990)
Vocal Pitch$_t$	−0.111***	−0.025***
	(0.028)	(0.005)
"Women" Percent$_t$ × Vocal Pitch$_t$	13.833**	1.285
	(5.909)	(1.094)
N	4,854	4,854
Log Lik	−9,887.093	−1,769.599
AIC	19,786.190	3,551.198

(b) Vocal Pitch$_{t+1}$

	Dependent variable:	
	Same Votes	Same Percent
	(3)	(4)
Constant	2.222***	0.601***
	(0.030)	(0.006)
"Women" Percent$_{t+1}$	2.684	−0.166
	(2.342)	(0.419)
Vocal Pitch$_{t+1}$	0.040	−0.002
	(0.028)	(0.005)
"Women" Percent$_{t+1}$ Vocal Pitch$_{t+1}$	1.307	0.160
	(2.572)	(0.467)
N	4,853	4,853
Log Lik	−9,895.375	−1,785.202
AIC	19,802.750	3,582.405

Note: In Panel A, `Same Votes` is the number of times the subsequent male MC ($t+1$) voted in the same direction as the female MC (t). In `Same Percent`, we divide `Same Votes` by the total number of votes on that legislative day. Results are reprinted from Model 1 in Tables S27 and S28. In Panel B, the dependent variables are the same, but we re-estimate those models using the total number of times the male MC used one of the Pearson and Dancey (2011*b*) terms divided by the total number of words in the speech (`''Women'' Percent`$_{t+1}$) with the male MC's standardized vocal pitch (`Vocal Pitch`$_{t+1}$). Ultimately, this tests whether the voting patterns outlined in Tables S27 and S28 can be attributed to the male MC generally talking about women with emotional intensity. These models report the results from a multilevel linear regression. All models also include a randomly varying intercept for each dyad. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

vocal pitch is higher than the speaker preceding her, our results are consistent with those reported above: a subsequent male MC casts a greater percentage of his votes with the female MC preceding him (t) when she speaks with intensity (Vocal Pitch$_t$) about women ("Women" Percent$_t$).

Taken together, these dyadic models are generally supportive of the results we present in the main text. When we account for the temporal ordering of speeches, in six of our eight models we reach the same conclusions as our main findings. Given that our theoretical expectations focus on large numbers of female MCs speaking with intensity about women – and modeling men's responses in a dyadic framework is thus a conservative test of the impact of female speech – we find these results encouraging.

Because we are using observational data, we cannot make causal claims about the effect of female MCs' emotionally intense speeches about women on their male colleagues. We have attempted to rule out, however, a backlash to these speeches from male MCs. The dyadic models presented above leverage the temporal ordering of speeches and show that there is a consistent, and positive, relationship between the emotional intensity of female MCs' speeches about women and subsequent male MCs' behavior. Below, we present a series of placebo tests to help rule out alternative explanations for this correlation. Our first two placebo tests attempt to account for the possibility that men who take the floor after an emotionally intense female speech would likely vote in line with the preceding female speaker irrespective of the intensity of her speech. We thus estimate new dyadic models that replicate those described above, but predict men's voting behavior using their own vocal pitch and references to women, rather than that of the preceding female MC. Our final placebo test predicts male MCs' behavior based on the emotional intensity of a *subsequent* female MCs' speech about women.[10]

Table S29 reports the first of our placebo tests. Models 1 and 2 in Panel A show the results we obtained in Table S27, Model 1 and Table S28, Model 1, respectively. Recall that these are the predicted effect of a female MC's emotional intensity ($\texttt{Vocal Pitch}_t$) and references to women ($\texttt{``Women'' Percent}_t$) on a subsequent male speaker's voting behavior. Models 3 and 4 in Panel B show our re-estimated placebo test. Here, we predict a male MC's number and percentage of votes cast in the same direction as the preceding female speaker based on that MC's emotional intensity ($\texttt{Vocal Pitch}_{t+1}$) and references to women ($\texttt{``Women'' Percent}_{t+1}$). Based on this model, we find that a male MC's vocal pitch and references to women does not predict either the number of votes cast (Model 3) or percentage of votes cast (Model 4) with the female MC speaking immediately before him. This suggests that the dyadic results we presented in Tables S27 and S28 are not simply due to men who are already intense in their discussion of women taking to the floor following an emotionally intense speech given by a female colleague.

We show a second placebo test in Table S30. In this test, we reproduce the results from Model 3 of Tables S27 and S28 in columns 1 and 2. These models are the predicted effect of a female MC's emotional intensity ($\texttt{Vocal Pitch}_t$ - $\texttt{Vocal Pitch}_{t-1}$) and references to women relative to a previous speaker ($\texttt{``Women'' Percent}_t$ - $\texttt{``Women'' Percent}_{t-1}$) on a subsequent male speaker's voting behavior. Columns 3 and 4 report our placebo test. These models predict a male speaker's number and percentage of votes cast in the same direction as the preceding female speaker based on his emotional intensity ($\texttt{Vocal Pitch}_{t+1}$) and references to women ($\texttt{``Women'' Percent}_{t+1}$), relative to those of the speaker before last. As before, we find no significant effects of male MC's own vocal pitch or references to women on their likelihood of voting with a preceding female speaker.

We present a third set of placebo tests in Table S31. The dependent variable in Models 1, 2, 5, and 6 (`Same Votes`) is the raw number of times the male speaker at time $t-1$ cast the same vote as a female speaker at time t on that legislative day. In Models 3, 4, 7, and 8 the dependent variable is the raw votes cast in the same direction divided by the total number of votes on that day (`Same Percent`). In both models, we predict male voting behavior at time $t-1$ using the percent of references to women and the vocal pitch of a female MC's speech

[10]We thank an anonymous reviewer for suggesting this test.

Table S30: Effect of Quantity and Intensity of Women's Speech on Men's Voting Patterns (Placebo #2)

(a) Vocal Pitch_t -Vocal Pitch_{t-1}

	Dependent variable:	
	Same Votes	Same Percent
	(1)	(2)
Constant	2.232***	0.602***
	(0.030)	(0.006)
"Women" Percent_t	−9.499*	−2.201**
	(5.359)	(0.988)
Vocal Pitch_t - Vocal Pitch_{t-1}	−0.106***	−0.012***
	(0.021)	(0.004)
"Women" Percent_t × (Vocal Pitch_t - Vocal Pitch_{t-1})	13.956***	1.779**
	(4.942)	(0.903)
N	4,851	4,851
Log Lik	−9,875.795	−1,775.689
AIC	19,763.590	3,563.377

(b) Vocal Pitch_{t+1} -Vocal Pitch_{t-1}

	Dependent variable:	
	Same Votes	Same Percent
	(3)	(4)
Constant	2.227***	0.601***
	(0.030)	(0.006)
"Women" Percent_{t+1}	2.616	−0.191
	(2.311)	(0.412)
Vocal Pitch_{t+1} - Vocal Pitch_{t-1})	−0.026	0.00003
	(0.021)	(0.004)
"Women" Percent_{t+1} × (Vocal Pitch_{t+1} - Vocal Pitch_{t-1})	3.436	0.576
	(2.308)	(0.411)
N	4,850	4,850
Log Lik	−9,889.605	−1,785.051
AIC	19,791.210	3,582.103

Note: In Panel A, `Same Votes` is the number of times the subsequent male MC ($t + 1$) voted in the same direction as the female MC (t). In `Same Percent`, we divide `Same Votes` by the total number of votes on that legislative day. Results are reprinted from Model 3 in Tables S27 and S28. In Panel B the dependent variables are the same, but we re-estimate those models using the total number of times the male MC used one of the Pearson and Dancey (2011*b*) terms divided by the total number of words in the speech (`‘‘Women’’ Percent`$_{t+1}$) with the male MC's standardized vocal pitch (`Vocal Pitch`$_{t+1}$) minus the standardized vocal pitch from the speaker who preceeded the female MC (`Vocal Pitch`$_{t-1}$). Ultimately, this tests whether the voting patterns outlined in Tables S27 and S28 can be attributed to the male MC generally talking about women with emotional intensity. These models report the results from a multilevel linear regression. All models also include a randomly varying intercept for each dyad. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Table S31: Effect of Subsequent Women's Speech on Prior Men's Behavior (Placebo #3)

(a) Vocal Pitch$_t$

	Dependent variable:			
	Same Votes		Same Percent	
	(1)	(2)	(3)	(4)
Constant	2.567***	3.927***	0.623***	0.953***
	(0.037)	(0.124)	(0.007)	(0.019)
"Women" Percent$_t$	−0.620	−1.732	0.019	−0.196
	(7.287)	(6.466)	(1.267)	(0.967)
Vocal Pitch$_t$	−0.088**	−0.064*	−0.024***	−0.016***
	(0.037)	(0.033)	(0.006)	(0.005)
"Women" Percent$_t$ × Vocal Pitch$_t$	8.644	8.517	0.964	0.741
	(8.688)	(7.709)	(1.512)	(1.153)
Controls		✓		✓
N	3,441	3,441	3,441	3,441
Log Lik	−7,325.411	−6,919.179	−1,312.693	−396.814
AIC	14,662.820	13,860.360	2,637.386	815.628

(b) Vocal Pitch$_t$ -Vocal Pitch$_{t-1}$

	Dependent variable:			
	Same Votes		Same Percent	
	(5)	(6)	(7)	(8)
Constant	2.550***	3.911***	0.619***	0.951***
	(0.037)	(0.124)	(0.007)	(0.019)
"Women" Percent$_t$	1.775	0.932	0.165	−0.030
	(7.068)	(6.266)	(1.230)	(0.938)
(Vocal Pitch$_t$ - Vocal Pitch$_{t-1}$)	−1.685	−0.224	−0.161	0.068
	(5.949)	(5.272)	(1.035)	(0.789)
"Women" Percent$_t$ × (Vocal Pitch$_t$ -Vocal Pitch$_{t-1}$)	−1.685	−0.224	−0.161	0.068
	(5.949)	(5.272)	(1.035)	(0.789)
Controls		✓		✓
N	3,437	3,437	3,437	3,437
Log Lik	−7,317.752	−6,908.878	−1,315.319	−399.691
AIC	14,647.500	13,839.750	2,642.637	821.381

Note: `Same Votes` is the number of times the previous male MC ($t-1$) voted in the same direction as the female MC (t). In `Same Percent`, we divide `Same Votes` by the total number of votes on that legislative day. In Panel A, the percentage of the female MC's speech dedicated to women references (``Women'' Percent$_t$) is interacted with her standardized vocal pitch (Vocal Pitch$_t$). In Panel B, the dependent variables are the same, but we subtract the previous male MC's standardized vocal pitch (Vocal Pitch$_{t-1}$). All models are multilevel linear regressions with randomly varying intercepts for each dyad. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

given at time t. In this way, we are predicting a male MC's behavior using the subsequent speech of a female MC. We present in Table S31 both models with and without the set of control variables used in Tables S26–S28.

Because there is no means for a speaker to affect a temporally prior speaker, we should expect these results to be null. If our models predict a statistical relationship between subsequent female MCs' speeches and prior male MCs' behavior, then it would suggest that our findings may be influenced by a spurious correlation. Said differently, combined with Placebo Test #1 and Placebo Test #2, this placebo test should detect whether male MCs would have voted in line with a female MC regardless of her speech's content. With our observational data we are unable to provide a direct test of any causal link between female MCs' speeches and men's behavior, but this placebo test should help us understand if there is substantial cause for concern about the interpretation of our main results.

Panel A presents our results predicting the previous male MC's voting behavior using a female MC's speech he has yet to hear. Beginning with Model 1, we see the interaction between the current female MC's references to women (`"Women" Percent`$_t$) and her emotional intensity (`Vocal Pitch`$_t$) is not statistically distinguishable from zero. This finding is robust to the inclusion of controls (Models 2 and 4) as well as to an alternative construction of our dependent variable (Models 3 and 4). Together, this suggests that prior male speakers are not being influenced by the female MCs that follow them. This stands in contrast to Model 1 in Table S27. In that model, we found a strong relationship between a female MC's emotionally intense speech about women and a subsequent male MC's voting behavior. In particular, the male MC was significantly more likely to vote in the same direction as the female speaker. Together, these findings are consistent with male MCs responding (and responding favorably) to previous female MCs who delivered emotionally intense speeches about women. They are not consistent with those male MCs simply being more likely to vote in line with female speakers regardless of their speech's content or emotional intensity.

We extend this placebo test in Panel B of Table S31. For this extension, rather than using the standardized vocal pitch for a subsequent female MC, we instead consider whether that female MC was speaking with more emotional intensity than the previous male MC. This helps to account for whether that female MC gave a particularly emotionally intense speech relative to the context in which it was delivered. It also parallels Model 3 in Table S28. Our results for this placebo test echo those presented in Panel A. There is no statistically significant relationship between a female MC's emotionally intense speech about women and prior male speakers' behavior. This again suggests that our main dyadic results are not simply picking up a spurious correlation between female MCs' emotionally intense speeches and male MCs' voting behavior, but are instead consistent with a potential response to female MCs' speeches.

Since we are relying exclusively on observational data, we cannot provide a direct test of a causal mechanism linking female MCs' emotionally intense speeches about women to male MCs' behavior. This is especially relevant for our analysis of voting, since the literature has long suggested that floor speeches have a limited (if any) effect on voting behavior. Our results here are not meant to contradict this finding. Instead, our aim is simply to determine whether there is a backlash when a large number of female MCs speak with emotional intensity about women. Past research has shown that as women become more prevalent in legislatures, male politicians act to minimize their influence in order to maintain dominance (Heath, Schwindt-Bayer and Taylor-Robinson 2005; Kanthak and Krause 2012; Krook 2015), including becoming more aggressive and controlling of deliberation (Kathlene 1994). For this reason, it is important to consider the possibility that male MCs may respond negatively to female MCs speaking with more intensity about women.

In the main text, we test whether there is any evidence of male backlash using the interaction between the total number of female speeches on women and their average vocal pitch. Using the standardized vote measure introduced in Section S6.1, we show in Table 7 that male MCs tend to vote more with female MCs when they collectively speak with more emotional intensity about women. The result is then replicated using an unstandardized vote measure in Section S6.2. We next re-estimated our main results including measures for male speech on women. These results are reported in Table S41. Regardless of the model, we find no evidence of male backlash. This suggests when female MCs speak with greater intensity about women, they do not seem to face any immediate detrimental effects.

Our dyadic models are meant to give additional support to this claim. We do not argue that a single speech can have a large influence on men's (or women's) behavior, nor do we make any strong claims about the persuasive effects of speech in general. Instead, we use the dyadic models outlined above—combined with the corresponding placebo tests—to demonstrate that their is no evidence of male backlash against female MCs. Across all of our models, the most consistent statistical relationship is between a female MC speaking about women with intensity and an increase in the subsequent male MC's likelihood of voting with her. Our placebo tests provide added confidence that this statistical relationship is not solely due to male speakers being more likely to vote with female speakers regardless of the content of their speeches. This should not, however, be misconstrued as determining that a single female MC's speech can be pivotal in persuading a male MC to vote in a particular direction. There are a multitude of factors that influence an MC's vote choice, originating both within and outside the legislative chamber, and we could not possibly hope to rule out all of these omitted variables. Instead, what we offer here is simply a test of whether our data provide evidence consistent or inconsistent with a male backlash against female MC's efforts to speak on behalf of women.

In sum, whether it is talking more about women (Pearson and Dancey 2011*b*) or "women's issues" (Gerrity, Osborn and Mendez 2007; Osborn and Mendez 2010), scholars have consistently shown that female representatives are more likely to elevate the voice of women both within (Pearson and Dancey 2011*a*) and beyond the halls of government (Herrnson, Lay and Stokes 2003). Our work suggests that such efforts do not lead to male backlash, which should give some comfort to gender and politics scholars who emphasize the importance of women's speech.

Table S32: Female MCs More Likely to Talk About Women, with Greater Intensity (No Outliers)

	Dependent variable:			
	"Women" Mentioned		Standardized Vocal Pitch	
	(1)	(2)	(3)	(4)
Fixed Effects				
Constant	−2.442***	−2.195***	−0.051***	0.054**
	(0.036)	(0.186)	(0.005)	(0.026)
Female	0.865***	0.783***	0.069***	0.052***
	(0.080)	(0.082)	(0.011)	(0.012)
"Women" Mentioned			0.018	−0.051***
			(0.014)	(0.014)
Female × "Women" Mentioned			0.060**	0.086***
			(0.013)	(0.013)
Controls		✓		✓
N_1	68,150	68,150	68,150	68,150
N_2	613	613	613	613
Log Likelihood	−21,837.380	−20,817.400	−85,688.450	−84,612.430
AIC	43,680.760	41,656.790	171,388.900	169,252.900

Note: Re-estimated the models from Table 1 only including speeches which had a standardized vocal pitch ±2 standard deviations. Controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

S8.3 Potential Outliers: Reduced Models

To address concerns that our results are being driven by a handful of influential and extreme speeches, we re-estimated all models in the main text eliminating potential outliers. To do so, we use a conservative definition of what constitutes an outlier: any speech with a vocal pitch more than ±2 standard deviations away from a speaker's baseline. We find that the substantive results we report in the main text remain unchanged even after restricting our data in this way.

Table S32 re-estimates Models 1-4 in Table 1 in the main text. As this table shows, our initial results are robust even after eliminating any speeches with very high or low vocal pitch relative to a speaker's baseline. Similar results can be found in Table S33, which re-estimates the models from Table 5 in the main text excluding days in which the average vocal pitch of female speeches on women is not within ±2 standard deviations of the mean. In the main text, the interaction between `Female Speeches` and `Female Pitch` was only statistically significant when additional controls were included in the model. We find the same in Table S33, suggesting the substantive interpretation is equivalent even when potential outliers are removed from the data.

Table S33: The Effect of Quantity and Intensity of Women's Speech on Quantity of Men's Speeches About Women (No Outliers)

	Dependent variable:	
	"Women" Mentioned	
	(1)	(2)
Fixed Effects		
Constant	-2.691^{***}	-2.210^{***}
	(0.041)	(0.221)
Female Speeches	0.056^{***}	0.061^{***}
	(0.003)	(0.003)
Female Pitch	-0.174^{***}	-0.170^{***}
	(0.034)	(0.035)
Female Speeches × Female Pitch	0.009	0.012^{*}
	(0.006)	(0.006)
Controls		✓
N_1	49,598	49,598
N_2	509	509
Log Likelihood	−14,572.020	−13,793.910
AIC	29,154.050	27,617.810

Note: Re-estimated the models from Table 5 only including speeches which had a standardized vocal pitch ±2 standard deviations. Controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

Table S34: The Effect of Quantity and Intensity of Women's Speech on Men's Vocal Pitch (No Outliers)

	Dependent variable:	
	Male Vocal Pitch	
	(1)	(2)
Constant	−0.020***	−0.023***
	(0.007)	(0.007)
"Women" Mentioned	0.020	0.023
	(0.022)	(0.022)
Female Speeches	0.001	0.004***
	(0.001)	(0.001)
Female Pitch	0.086***	0.080***
	(0.010)	(0.009)
"Women" Mentioned × Female Speeches	−0.001	−0.003
	(0.003)	(0.003)
"Women" Mentioned × Female Pitch	0.034	0.025
	(0.033)	(0.031)
Female Speeches × Female Pitch	0.020***	0.011***
	(0.002)	(0.002)
"Women" Mentioned × Female Speeches × Female Pitch	0.006	0.014***
	(0.005)	(0.005)
Random Effects		
MC	0.000	0.000
N_1	49,324	49,884
N_2	506	506
Log Likelihood	−69,035.120	−70,357.910
AIC	138,090.200	140,735.800

Note: Re-estimated the models from Table 6 only including speeches which had a standardized vocal pitch ±2 standard deviations. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

We also find generally consistent results when the dependent variable is male vocal pitch. This is shown in Table S34, which re-estimates the models from Table 6 in the main text. Even though the interaction between `Female Speeches`, `Female Pitch`, and `''Women'' Mentioned` is not statistically significant at the 0.05-level when speeches are restricted to ±2 standard deviations (see Model 1), the effect is in the same direction as our main result in Table 6. Moreover, when we relax our definition of an outlier to include only speeches that are ±3 standard deviations from the mean (see Model 2), we find results that are nearly identical to our main findings.

Finally, when potential outliers are excluded, we still find almost identical results to those presented in Table 7. Indeed, regardless of whether controls are (Model 2) or are not (Model 1) included, the results in Table S35 are essentially the same as those found in the main text. This suggest that our male vote results are not being driven by extreme cases in which

Table S35: Effect of Quantity and Intensity of Women's Speech on Men's Voting Patterns (No Outliers)

	Dependent variable:	
	Male Votes Cast	
	(1)	(2)
Fixed Effects		
Constant	0.021	0.096*
	(0.015)	(0.051)
Female Speeches	0.001	−0.00002
	(0.001)	(0.001)
Female Pitch	−0.184***	−0.176***
	(0.014)	(0.014)
Female Speeches × Female Pitch	0.015***	0.012***
	(0.002)	(0.002)
Controls		✓
N_1	21,769	21,769
N_2	485	485
Log Likelihood	−27,885.740	−27,870.470
AIC	55,783.480	55,770.930

Note: Re-estimated the models from Table 7 only including speeches which had a standardized vocal pitch ±2 standard deviations. Controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

female vocal pitch exceeds ±2 standard deviations when talking about women. Altogether, these robustness checks give us greater confidence that our main results are not dependent on a handful of extreme speeches or extreme speaking days where vocal pitch is far outside of the range we might expect in normal legislative discourse.

S8.4 Potential Confounders: Interacting CQ Bills and Women Bills

To address concerns regarding the legislative activities on a given day, we re-estimated the models found in Tables 5–7 including an interaction between `CQ Bills` and `Women Bills`. Here, the logic is relatively simple – female MCs might be especially likely to be emotionally intense when speaking about women on days where important legislation dealing with women's issues is being debated on the House floor. If this is the case, both male and female behavior may be explained by the bills being debated (rather than women's speech on women). Tables S36 and S37 attempt to gain traction on this question by including `CQ Bills` × `Women Bills` as an additional control.

Table S36 replicates our result from Table 5 with the inclusion of this new interaction term. Our results including this new interaction term are identical without controls; `Female`

Table S36: The Effect of Quantity and Intensity of Women's Speech on Quantity of Men's Speeches About Women (Women's Bills × CQ Bills)

	Dependent variable:	
	"Women" Mentioned	
	(1)	(2)
Fixed Effects		
Constant	-2.695^{***}	-2.219^{***}
	(0.041)	(0.220)
Female Speeches	0.056^{***}	0.059^{***}
	(0.003)	(0.003)
Female Pitch	-0.124^{***}	-0.124^{***}
	(0.031)	(0.032)
Women Bills		-0.042
		(0.031)
CQ Bills		-0.108^{***}
		(0.039)
Women Bills × CQ Bills		0.109^{*}
		(0.058)
Female Speeches × Female Pitch	0.009	0.009
	(0.005)	(0.006)
Additional Controls		✓
N_1	50,235	50,235
N_2	509	509
Log Likelihood	−14,735.510	−13,948.520
AIC	29,481.010	27,929.030

Note: Re-estimated the models from Table 5 including the interaction between `Women Bills` and `CQ Bills`. Additional controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

Table S37: Effect of Quantity and Intensity of Women's Speech on Men's Voting Patterns (Women Bills × CQ Bills)

	Dependent variable:	
	Male Votes Cast	
	(1)	(2)
Fixed Effects		
Constant	0.019	0.109**
	(0.015)	(0.051)
Female Speeches	0.001	−0.001
	(0.001)	(0.001)
Female Pitch	−0.187***	−0.176***
	(0.013)	(0.013)
Women Bills		0.048***
		(0.010)
CQ Bills		−0.030**
		(0.015)
Women Bills × CQ Bills		0.071***
		(0.023)
Female Speeches × Female Pitch	0.015***	0.011***
	(0.002)	(0.002)
Additional Controls		✓
N_1	21,920	21,920
N_2	485	485
Log Likelihood	−28,122.730	−28,103.140
AIC	56,257.460	56,238.280

Note: Re-estimated the models from Table 7 including the interaction between `Women Bills` and `CQ Bills`. Additional controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

`Pitch` and `Female Speeches` remain significant predictors of men's speech about women. In Model 2, however, the coefficient associated with the interaction term loses significance. However, the substantive effect is almost identical to that reported in the main text: 0.009 versus 0.011. Given the similarity to our main results, we remain confident that we are not simply picking up on the effect of important women's bills being on the agenda.

We are also able to replicate our findings for men's voting patterns. As shown in Model 2 of Table S37, our findings are nearly identical to those presented in Table 7. With the additional control for `Women Bills` × `CQ Bills`, our substantive results remain the same: `Female Pitch` and `Female Speeches` × `Female Pitch` remain statistically significant predictors of the likelihood of men voting with female speakers, and the magnitude of these coefficients is nearly identical.

The only findings we were unable to replicate with the inclusion of this additional control were those from Table 6 in the main text. Regardless of the specification, when `CQ Bills` was interacted with `Women Bills` the multilevel model failed to converge. Consequently, we cannot rule out this competing explanation for the effect of female speech on male vocal pitch. Still, the results presented here do not suggest that our main findings are being driven solely by the issues on the agenda. Rather, most of our results appear robust even when accounting for the interaction between important bills and bills concerning women.

S8.5 Potential Confounders: Questions

Throughout our paper, we argue that subtle changes in vocal pitch are indicative of emotional intensity (or activation), and our validation exercises presented in Section S2 above support that argument. Still, it is important to note that changes in vocal pitch can also be indicative of other linguistic features. For example, English speakers typically increase their vocal pitch at the end of a sentence to denote a question. This phenomenon (rising pitch tail) could contribute to the increase in vocal pitch we observe among legislators. In this section, we control for changes in vocal pitch associated with questions by re-estimating our models from the main text including a control for whether the speech included a question. We identify questions in speeches using the text of the speeches – any speech that included a question mark was coded as 1 on the `Question` variable. As we present below, our results are robust to the inclusion of this control.

Table S38 replicates our original results from Table 1. Our results here are the same. In Model S38.2, we see that `Female` remains statistically significant with a comparable magnitude after the inclusion of our control for speeches with questions. In Model S38.4, we find that the interaction term between `Female` and `''Women'' Mentioned` remains statistically significant, and the magnitude of the replicated results (0.103) is substantively similar to our original results (0.112).

Our results for men's quantity of speeches about women are similarly robust to the inclusion of this new control. In Table S39, we re-estimate our models from Table 5 and are primarily interested in the interaction between `Female Speeches` and `Female Pitch`. As in our main results, this interaction term is positive and statistically significant, with a substantive magnitude (0.012) that is nearly identical to our original result (0.011). These findings together suggest that our main results for women's speeches cannot be attributed to the rising pitch tail associated with questions.

We next consider whether the results reported in Table 6 are robust to the inclusion of a control for speeches including a question. As shown in Table S40, all of our key independent variables remain essentially unchanged from the main text; male MCs' vocal pitch is significantly higher when referencing women on days in which a large number of female MCs gave emotionally intense speeches about women. With the inclusion of this control, the coefficient on this interaction term is 0.013, almost identical to the 0.016 reported in the main text. As with our preceding analyses, this suggest that questions are not driving the higher pitch we observe in male MCs' responses to female MCs' speech.

Table S38: Female MCs More Likely to Talk About Women, with Greater Intensity (Controlling for Questions)

	Dependent variable:			
	"Women" Mentioned		Standardized Vocal Pitch	
	(1)	(2)	(3)	(4)
Fixed Effects				
Constant	−2.427***	−2.190***	−0.002	0.063***
	(0.035)	(0.183)	(0.004)	(0.024)
Female	0.866***	0.787***	−0.017	−0.022**
	(0.078)	(0.081)	(0.011)	(0.011)
Question		−0.107***		0.370***
		(0.030)		(0.009)
"Women" Mentioned			0.020	−0.040***
			(0.014)	(0.014)
Female × "Women" Mentioned			0.090***	0.103***
			(0.027)	(0.026)
Additional Controls		✓		✓
N_1	74,151	74,151	71,198	71,198
N_2	619	619	613	613
Log Likelihood	−23,909.700	−22,780.610	−100,720.100	−98,736.320
AIC	47,825.410	45,585.210	201,452.100	197,502.600

Note: Re-estimated models from Table 1 in the main text including a dummy variable for whether the speech included a question. Additional controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

Table S39: The Effect of Quantity and Intensity of Women's Speech on Quantity of Men's Speeches About Women (Controlling for Questions)

	Dependent variable:	
	"Women" Mentioned	
	(1)	(2)
Fixed Effects		
Constant	-2.695^{***}	-2.216^{***}
	(0.041)	(0.219)
Female Speeches	0.056^{***}	0.060^{***}
	(0.003)	(0.003)
Female Pitch	-0.124^{***}	-0.128^{***}
	(0.031)	(0.032)
Question		-0.086^{**}
		(0.039)
Female Speeches × Female Pitch	0.009	0.012^{**}
	(0.005)	(0.006)
Additional Controls		✓
N_1	50,235	50,235
N_2	509	509
Log Likelihood	−14,735.510	−13,947.810
AIC	29,481.010	27,927.620

Note: Re-estimated models from Table 5 in the main text including a dummy variable for whether the speech included a question. Additional controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

Table S40: The Effect of Quantity and Intensity of Women's Speech on Men's Vocal Pitch (Controlling for Questions)

	Dependent variable:	
	Male Vocal Pitch	
	(1)	(2)
Fixed Effects		
Constant	-0.022^{***}	0.029
	(0.007)	(0.030)
"Women" Mentioned	0.026	-0.028
	(0.022)	(0.022)
Female Speeches	0.003^{***}	0.004^{***}
	(0.001)	(0.001)
Female Pitch	0.077^{***}	0.072^{***}
	(0.009)	(0.009)
Question		0.354^{***}
		(0.010)
"Women" Mentioned × Female Speeches	-0.003	-0.003
	(0.003)	(0.003)
"Women" Mentioned × Female Pitch	0.004	0.004
	(0.031)	(0.030)
Female Speeches × Female Pitch	0.012^{***}	0.010^{***}
	(0.002)	(0.002)
"Women" Mentioned × Female Speeches × Female Pitch	0.016^{***}	0.013^{**}
	(0.005)	(0.005)
Additional Controls		✓
N_1	49,914	49,914
N_2	506	506
Log Likelihood	$-70,478.580$	$-69,255.900$
AIC	140,977.200	138,553.800

Note: Re-estimated models from Table 6 in the main text including a dummy variable for whether the speech included a question. Additional controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Altogether, these findings are consistent with vocal pitch capturing an important aspect of emotions in speech. We acknowledge that vocal pitch may indicate other linguistic features – such as questions – in ordinary speech. However, it is clear from these results that we are not simply detecting the effects of questioning sentences in speeches. And there is no reason to believe that increased vocal pitch over the entire duration of a speech has linguistic value in the same way that rising pitch tail conveys a query to an English speaker. For this reason, these robustness checks give us greater confidence that our measure of vocal pitch is detecting larger shifts in emotional content, rather than smaller linguistic features of sentences.

S8.6 Potential Confounders: Men Speaking About Women

On pages 26–27 in the main text, we argue that a large number of female MCs speaking intensely about women could affect Congressmen's behavior. Since we are relaying on observational data, we cannot establish a clear causal relationship, but we are able to present a series of models showing a clear relationship between female MCs' speaking behavior and male MCs' voting behavior. Specifically, we show that on legislative days when many female MCs give emotionally intense speeches about women, male MCs are more likely to cast votes in the same direction as those female MCs. In this section, we examine whether we see a similar relationship between when *male MCs* give emotionally intense speeches about women and men's voting behavior. As we show below, our results in the main text are robust to the inclusion of male MCs' speaking behavior, suggesting a unique relationship between female MCs' speeches about women and male MCs' voting behavior.

Table S41 shows our replication of Table 7 from the main text with the addition of the number and vocal pitch of male MCs' speeches about women. In both Models 1 and 2, our original findings are robust to the inclusion of men's speaking behavior as a predictor of men's votes. Specifically, our original coefficient for `Female Pitch` in Model 1 was -0.187, which increases to -0.207 after including controls for male MCs' speaking behavior. We similarly find robust results for the interaction between `Female Speeches` and `Female Pitch`. This suggests that the results reported in Table 7 in the main text are robust even after accounting for male speaking behavior, and indeed appear to be conservative estimates of the coefficients for women's speaking behavior.

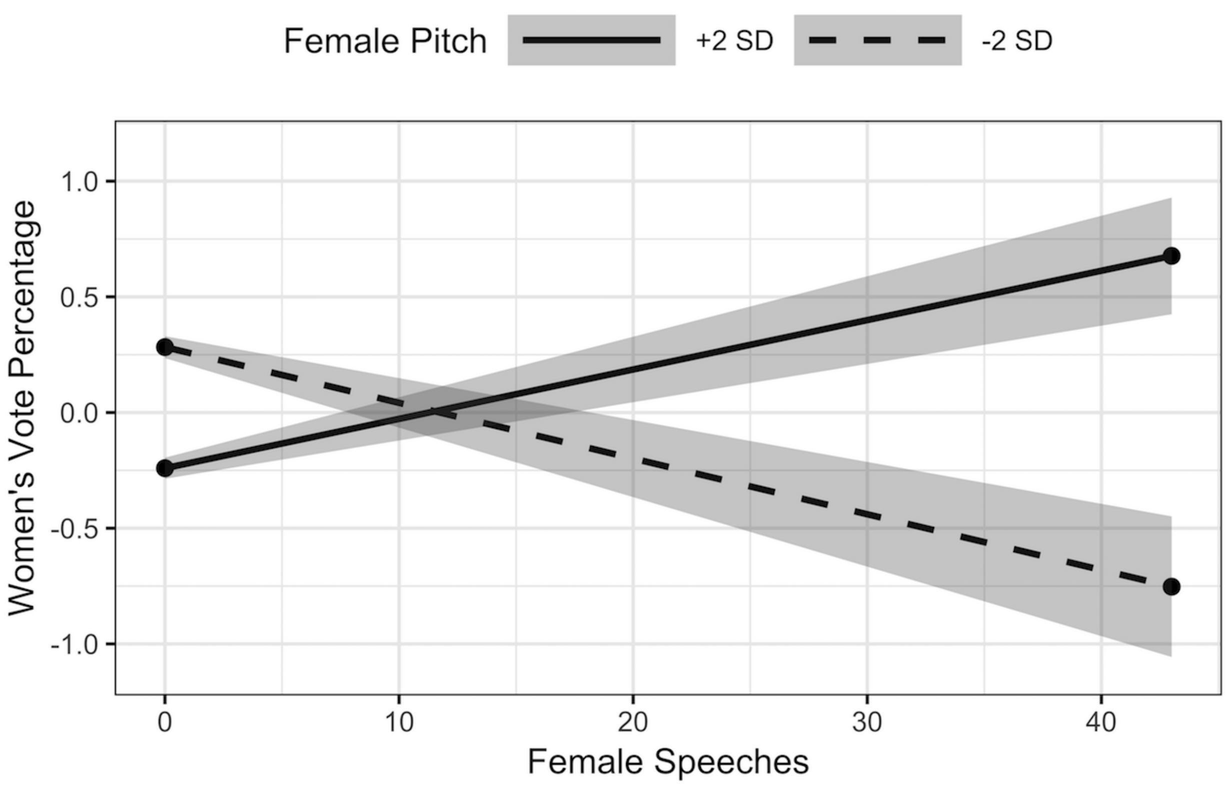
Also worth noting is that the interaction between *Male Speeches* and *Male Pitch* has a negative relationship with the degree to which male MCs vote in the same direction as female MCs. In both our original findings and the results presented here, we find that when many female MCs give emotionally intense speeches about women, male MCs are more likely to vote in the same direction as female MCs. Indeed, if we compare Figure S12 to Figure 3 in the main text, we see an essentially unchanged relationship between female MCs' speeches and male MCs' voting behavior. In Figure S13, however, we see a very different relationship between male MCs' speeches about women and male MCs' voting behavior. Here, the y-axis is the same as in Figure S12, but the x-axis is the number of male speeches referencing women. The solid line shows the predicted effect with male vocal pitch set at two standard

Table S41: Relationship between Women's Speech and Men's Voting Patterns (Controlling for Male Speeches)

	Dependent variable:	
	Male Votes Cast	
	(1)	(2)
Fixed Effects		
Constant	-0.011	0.107
	(0.016)	(0.079)
Female Speeches	-0.001	-0.002
	(0.002)	(0.002)
Female Pitch	-0.207^{***}	-0.195^{***}
	(0.013)	(0.014)
Male Speeches	0.004^{***}	0.004^{***}
	(0.001)	(0.001)
Male Pitch	-0.006	-0.022
	(0.019)	(0.019)
Female Speeches × Female Pitch	0.019^{***}	0.017^{***}
	(0.002)	(0.002)
Male Speeches × Male Pitch	-0.005^{***}	-0.005^{**}
	(0.002)	(0.002)
Additional Controls		✓
N_1	21,614	21,614
N_2	509	509
Log Likelihood	$-27{,}702.840$	$-27{,}687.190$
AIC	55,423.680	55,412.370

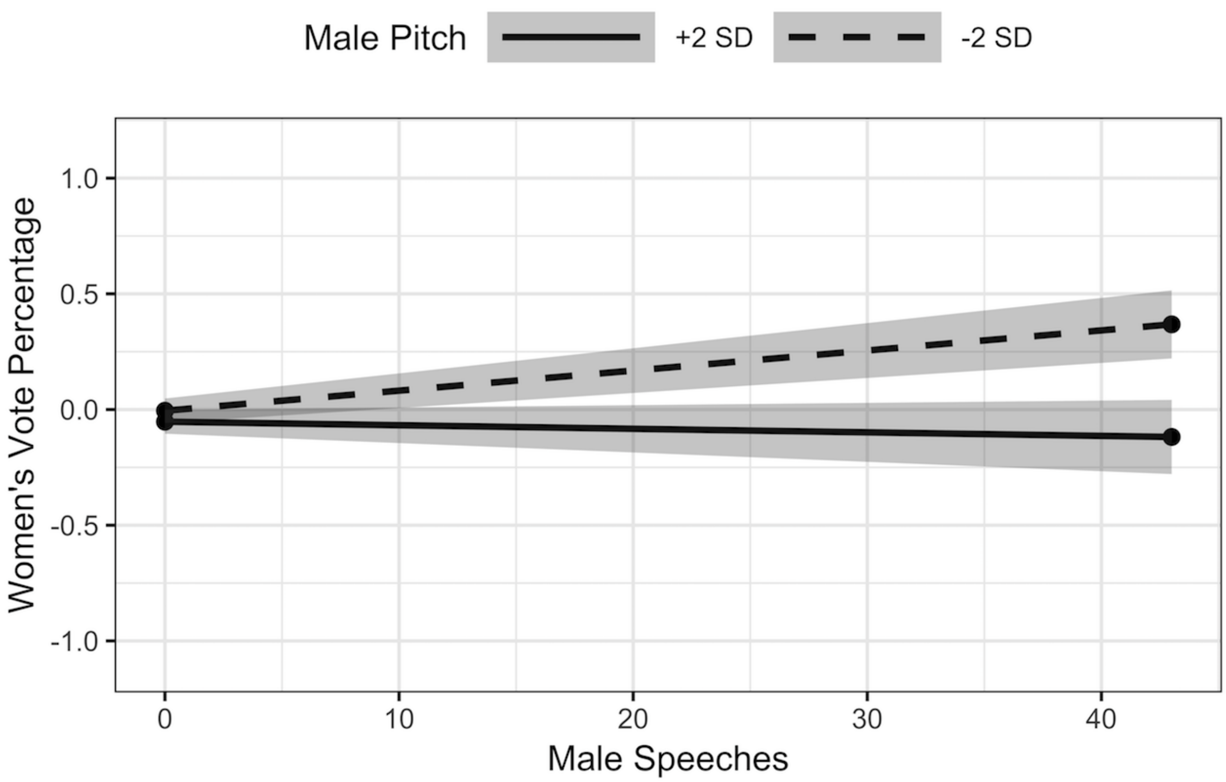
Note: Re-estimated models from Table 5 in the main text including the interaction between the number of male speeches mentioning women and the average vocal pitch of those speeches. Additional controls excluded to save space. Full models available upon request. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

Figure S12: Relationship between Women's Speech and Men's Voting Patterns (Controlling for Male Speeches)



Note: Predicted male voting behavior from Model 2 in Table S41 holding all other variables constant. Solid and dashed lines indicate `Female Pitch` was set to two standard deviations above (1.41) and below (-1.28) the mean respectively. On the x-axis `Female Speeches` is allowed to vary from its minimum (0) to maximum (43). The y-axis has the percentage of time the male MC voted with women, as described on pages S36–S41. The gray ribbons represent 95 percent confidence intervals.

Figure S13: The Quantity and Intensity of Women's Speech Affects Men's Voting Patterns



Note: Predicted male voting behavior from Model 2 in Table S41 holding all other variables constant. Solid and dashed lines indicate `Male Pitch` was set to two standard deviations above (1.13) and below (-1.01) the mean respectively. On the x-axis `Male Speeches` is allowed to vary from its minimum (0) to maximum (55). The y-axis has the percentage of time the male MC voted with women, as described on pages S36–S41. The gray ribbons represent 95 percent confidence intervals.

deviations above the mean, and the dashed line shows the predicted effect with male vocal pitch set at two standard deviations below the mean. What the solid line shows is that as many male MCs give emotionally intense speeches about women, the percentage of votes cast in the same direction as female MCs is essentially unchanged (and perhaps slightly lower). This suggests that the positive relationship we see between emotionally intense speeches about women and male MCs' voting behavior is unique to female MCs' speeches. This is entirely consistent with our argument about the importance of women's presence in legislative discourse.

S8.7 Potential Confounders: Expertise

The intensity of female MCs' speech about women could be influenced by their level of expertise. That is, the changes we observe in female MCs' vocal pitch when speaking about women might represent their greater confidence in speaking, rather than an underlying emotional commitment to representing women. Although we think it is likely that female MCs who speak intensely about women are also likely to have expertise on women's issues, in this section we test whether changes in vocal pitch can be captured by variables that measure expertise, including the number of women's bills introduced and the average interest group rating.

Table S42: Female MCs More Likely to Talk with Greater Intensity About Women (Controlling for the Number of Women's Bills Introduced)

	Dependent variable:			
	Standardized Vocal Pitch		Standardized Vocal Pitch	
	(1)	(2)	(3)	(4)
Fixed Effects				
Constant	-2.427^{***}	-2.218^{***}	-0.002	0.151^{***}
	(0.035)	(0.183)	(0.004)	(0.024)
Female	-0.020^{*}	-0.032^{***}	-0.014	-0.028^{**}
	(0.011)	(0.011)	(0.011)	(0.011)
Women's Bills Introduced	0.006	0.002	0.011^{**}	0.005
	(0.004)	(0.004)	(0.005)	(0.005)
"Women" Mentioned	0.019	-0.056^{***}	0.016	-0.057^{***}
	(0.015)	(0.015)	(0.015)	(0.015)
Female × "Women" Mentioned	0.090^{***}	0.113^{***}	0.070^{**}	0.091^{***}
	(0.027)	(0.027)	(0.029)	(0.029)
Female × Women's Bills Introduced			-0.026^{***}	-0.019^{**}
			(0.010)	(0.010)
"Women" Mentioned × Women's Bills Introduced			-0.026^{***}	-0.019^{**}
			(0.010)	(0.010)
Female × "Women" Mentioned × Women's Bills Introduced			0.076^{***}	0.068^{***}
			(0.025)	(0.024)
Additional Controls		✓		✓
N_1	69,644	69,644	69,644	69,644
N_2	588	588	588	588
Log Likelihood	−98,531.450	−97,494.600	−98,535.470	−97,500.110
AIC	197,076.900	195,019.200	197,090.900	195,036.200

Note: Re-estimating Models 3 and 4 from Table 1 in the main text including the number of bills sponsored which deal with women's issues as defined by Volden, Wiseman and Wittmer (2016). Additional controls excluded to save space. Full models available upon request. `Women's Bills Introduced` is standardized using the mean and standard deviation from each Congress. More details can be found on pages S80–S81. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

We begin with Table S42. Here, we include a variable that captures the total number of women's bills introduced by each MC. We define "women's bills" using the issues outlined by Volden, Wiseman and Wittmer (2016) (see page 28 in the main text). We next determine the number of bills each MC sponsors in a given Congress that fall into the major topic areas defined by Volden, Wiseman and Wittmer (2016). We then divide this sum by the total number of bills the MC sponsored in the same Congress. For example, Rep. Rosa DeLauro (D-CT) sponsored 207 bills in the 111th Congress of which 46 addressed women's issues. This means that 22.22 percent of the bills she sponsored in the 111th Congress fell into at least one of the major topic areas defined by Volden, Wiseman and Wittmer (2016).

We create a different measure for each Congress, as some terms are likely more conducive to the advancement of women's issues than others. We then standardize the percentage of women's bills using the mean and standard deviation for a given Congress. We call this variable `Women's Bills Introduced`. Here, positive values indicate MCs introduced more women's bills than we would expect given the percentage of women's bills introduced that Congress. Conversely, negative values suggest MCs were below average in terms of the percentage of their sponsored bills addressing women's issues.[11]

We present the results in Table S42. In Models 1 and 2, we include `Women's Bills Introduced` as a control variable. We find essentially the same results as those presented in the main text. The coefficient for the interaction between `Female` and `‘‘Women’’ Mentioned` is unchanged when `Women's Bills Introduced` is included as a control. This provides strong evidence that vocal pitch and the number of women's bills introduced are not interchangeable, which suggests we are capturing something new with our measure of emotional intensity.

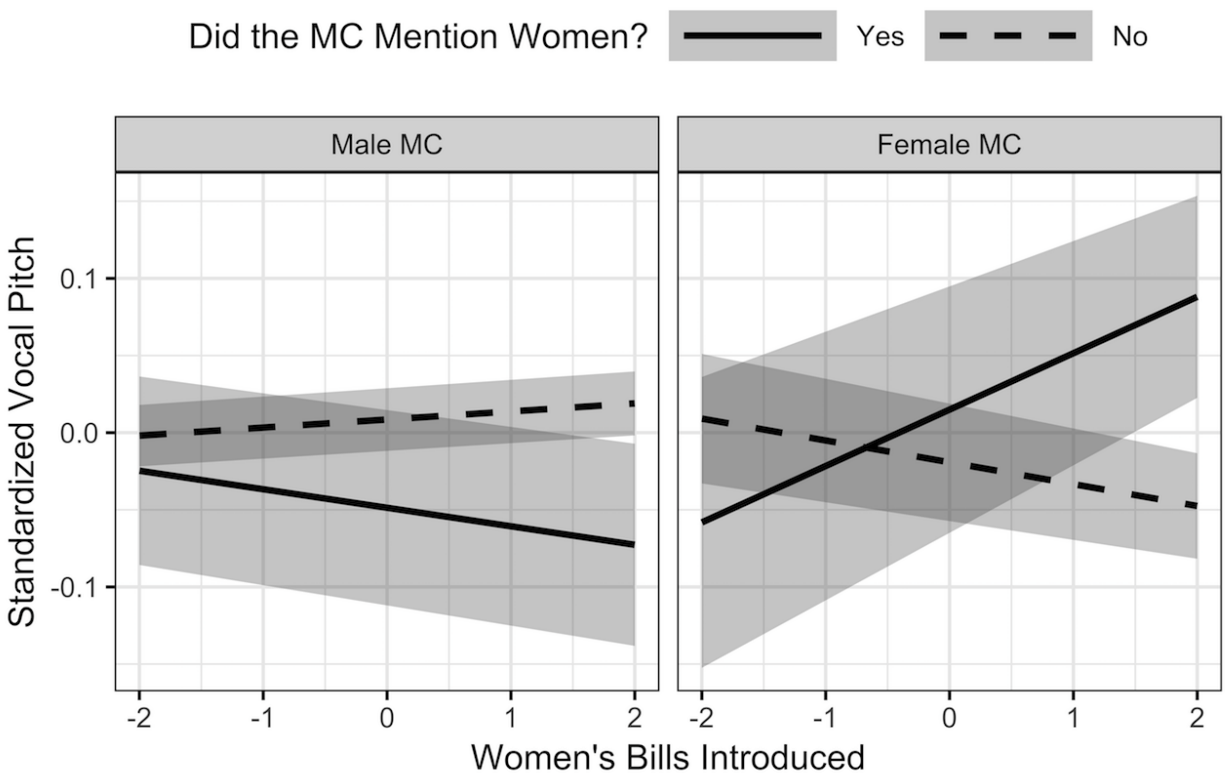
In Models 3 and 4 we interact our measure of emotional intensity with the number of women's bills introduced. These models test whether female MCs who introduce more women's bills also speak about women with greater emotional intensity. Although the interaction between `Female`, `‘‘Women’’ Mentioned`, and `Women's Bills Introduce` is positive and statistically significant at the 0.001-level, it is difficult to directly interpret the coefficient. Figure S14 thus reports predicted values when `Women's Bills Introduced` is allowed to vary ± 2 standard deviations.

When both `Female` and `‘‘Women’’ Mentioned` are set to 1, MCs' are predicted to speak at a higher vocal pitch as `Women's Bills Introduced` increases. Said differently, female MCs who introduce more women's bills tend to speak with *more* emotional intensity when speaking about women. The dashed line also shows the inverse is true when these female legislators do not mention women. That is, Congresswomen who introduce more women's bills tend to speak with *less* emotional intensity when `‘‘Women’’ Mentioned` is set to 0. Not only is this result consistent with our broader argument, but it also demonstrates that vocal pitch may yield additional insights when used in conjunction with more traditional variables (such as the percentage of sponsored bills which deal with women's issues). Regardless, these results provide strong evidence that the number of women's bills introduced (i.e., confidence/expertise) is not a substitute for our vocal pitch measure.

In Table S43, we conduct a similar analysis, except instead of including `Women's Bills Introduced` as a control we use the women's interest group ratings we describe on page 19 in the main text. More specifically, for each MC we computed the average score from the 24 groups outlined in Table S4 for a given Congress. Similar to `Women's Bills Introduced`, we standardized this measure using the mean and standard deviation for a given Congress. We call this variable `Women's Group Rating`. Here, positive (negative) values imply MCs cast more (fewer) votes in the preferred direction of the 24 groups as compared to the average

[11] This standardization means that the results outlined in Table S42 are on the same scale as those outlined in Table S43. As women's bills and women's interest group ratings are on different scales, this standardization is needed in order to make these two sets of results more comparable.

Figure S14: Intensity of Speeches about Women by Number of Women's Bills Introduced



Note: Predicted vocal pitch derived from Model 4 in Table S42 holding all other variables constant. Solid lines indicate the speech included at least one of the Pearson and Dancey (2011*b*) women's dictionary terms. Dashed lines indicate all other speeches. For a given MC, `Women's Bills Introduced` captures whether an MC (as compared to the rest of the Congress) tended to dedicate a greater percentage of his/her sponsored bills to women's issues. More details can be found on pages S80–S81. On the x-axis, `Women's Bills Introduced` is allowed to vary from ± 2 standard deviations. The y-axis reports the predicted standardized vocal pitch with positive values implying greater emotional intensity. The gray ribbons represent 95 percent confidence intervals.

Table S43: Female MCs More Likely to Talk with Greater Intensity About Women (Controlling for Women's Interest Group Ratings)

	Dependent variable:			
	Standardized Vocal Pitch		Standardized Vocal Pitch	
	(1)	(2)	(3)	(4)
Fixed Effects				
Constant	-2.427^{***}	-2.218^{***}	-0.002	0.151^{***}
	(0.035)	(0.183)	(0.004)	(0.024)
Female	-0.014	-0.031^{***}	-0.010	-0.025^{**}
	(0.011)	(0.011)	(0.011)	(0.011)
Women's Group Rating	-0.008^{**}	-0.019^{***}	-0.010^{**}	-0.021^{***}
	(0.004)	(0.006)	(0.004)	(0.007)
"Women" Mentioned	0.020	-0.054^{***}	0.021	-0.054^{***}
	(0.014)	(0.015)	(0.014)	(0.015)
Female × "Women" Mentioned	0.090^{***}	0.111^{***}	0.042	0.064^{**}
	(0.027)	(0.027)	(0.030)	(0.029)
Female × Women's Group Rating			-0.008	-0.014
			(0.011)	(0.011)
"Women" Mentioned × Women's Group Rating			0.009	0.012
			(0.015)	(0.014)
Female × "Women" Mentioned × Women's Group Rating			0.095^{***}	0.090^{***}
			(0.030)	(0.029)
Additional Controls		✓		✓
N_1	71,154	71,154	71,154	71,154
N_2	612	612	612	612
Log Likelihood	$-100,650.600$	$-99,570.690$	$-100,651.700$	$-99,572.040$
AIC	201,315.100	199,171.400	201,323.400	199,180.100

Note: Re-estimating Models 3 and 4 from Table 1 in the main text including the average women's interest group rating. Additional controls excluded to save space. Full models available upon request. `Women's Group Rating` is standardized using the mean and standard deviation from each Congress. More details can be found on page S81. Levels of significance are reported as follows: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Standard errors are reported in parentheses.

MC for that Congress. Again, this make the results outlined in Tables S42 and S43 more comparable.

We present the results in Table S43. In Models 1 and 2 we simply include `Women's Group Rating` as a control variable. When the coefficient for the interaction between `Female` and `''Women'' Mentioned` is compared to the original coefficient we report in Table 1 in the main text, we again find essentially the same results. This once again provides strong evidence that vocal pitch and confidence/expertise (here, as captured by women's interest group ratings) are not interchangeable.

In Models 3 and 4 we interact our measure of emotional intensity with the average women's interest group rating. This tests whether female MCs who tend to vote in the preferred direction of women's interests groups also tend to speak with more intensity when referencing women. The positive and significant coefficient associated with the interaction between `Female`, `''Women'' Mentioned`, and `Women's Group Rating` suggests that the interaction with `Women's Group Rating` likely functions similarly to the interaction with `Women's Bills Introduced`. We again plot predicted values to make the interaction more interpretable. These results are reported in Figure S15.

Beginning with the right panel, when both `Female` and `''Women'' Mentioned` are set to 1, female MCs are predicted to speak at a higher vocal pitch as `Women's Group Rating` increases. Said differently, female MCs who tend to vote in the preferred direction of women's interest groups also speak with *more* emotional intensity when talking about women. The dashed line also shows the inverse is true when they do not mention women. That is, Congresswomen who vote with women's interest groups tend to speak with *less* emotional intensity when `''Women'' Mentioned` is set to 0. Not only is this result consistent with what we found with `Women's Bills Introduced`, but it again demonstrates that vocal pitch may yield additional insights when used in conjunction with more traditional variables. Regardless, these results provide additional evidence consistent with our broader theoretical argument.

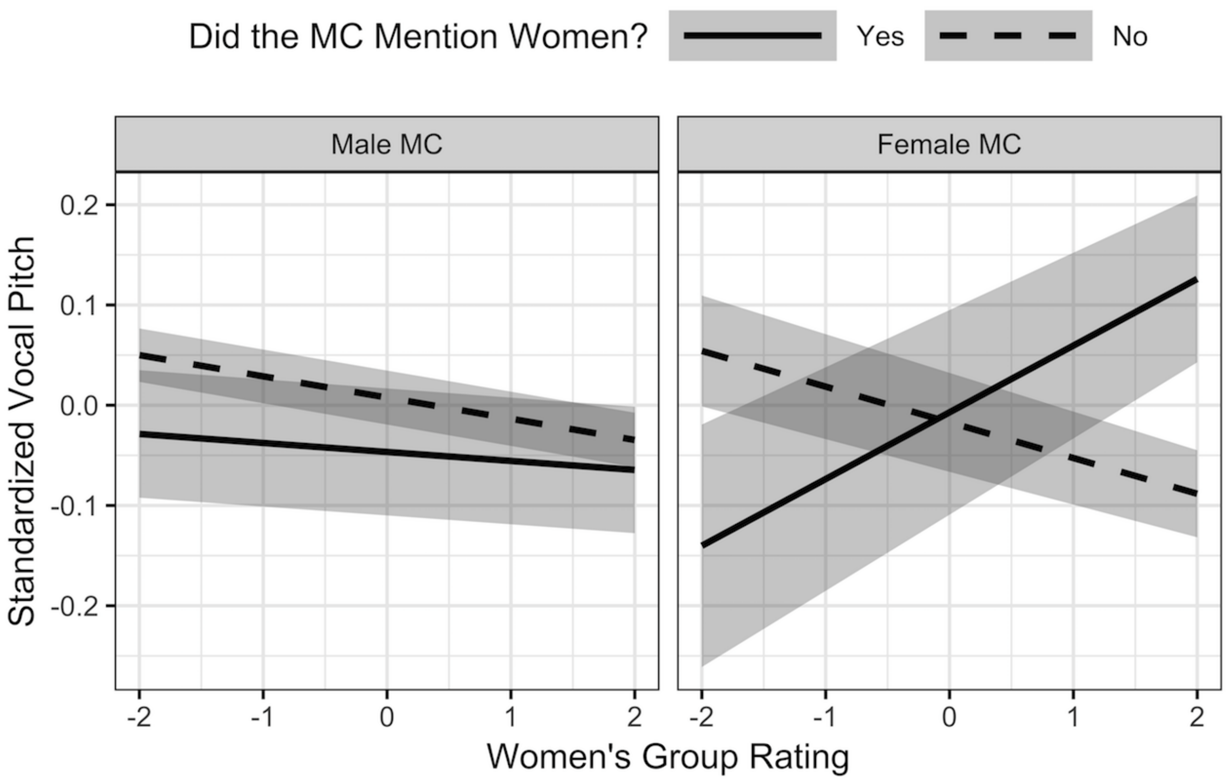
S8.8 Potential Confounders: Anxiety

As we explain in Section S2.1, emotions can be characterized as a mixture of two dimensions: a valence dimension and an arousal/activation/intensity dimension. As we argue in our paper, heightened vocal pitch is a useful indicator of this second dimension—arousal/activation/intensity—because when we are in this state our heart naturally begins to race and our muscles, including our vocal cords, tighten. The latter causes our vocal pitch to increase, which is why scholars use pitch to measure the intensity of emotional expressions. However, one may be concerned that we are detecting only emotional anxiety about speaking on the House floor, rather than emotions related to the topic of the speech.[12]

We do not believe, however, that more emotionally intense speeches simply reflect an

[12] We thank a helpful reviewer for pushing us on this point.

Figure S15: Intensity of Speeches about Women by Women's Interest Group Rating



Note: Predicted vocal pitch derived from Model 4 in Table S43 holding all other variables constant. Solid lines indicate the speech included at least one of the Pearson and Dancey (2011*b*) women's dictionary terms. Dashed lines indicate all other speeches. For a given MC, `Women's Group Rating` captures whether s/he was more likely than the average legislator to vote in the preferred direction of the 24 women's interest groups outlined in Table S4. More details can be found on page S81. On the x-axis, `Women's Group Rating` is allowed to vary from ± 2 standard deviations. The y-axis reports the predicted standardized vocal pitch with positive values implying greater emotional intensity. The gray ribbons represent 95 percent confidence intervals.

anxiety about speaking on the subject of the speech. In Table 4 we show that legislators speak with higher vocal pitch on issues owned by their party, and decreased pitch on issues owned by the opposing party. It is highly unlikely that this reflects lawmakers' greater anxiety when speaking about owned issues. Indeed, this would run counter to scholarship on issue ownership by Petrocik and others (Petrocik 1996; Petrocik, Benoit and Hansen 2003), which assumes that partisans advance party issues because they are thought to be better able to handle them.

We also address the concern that we might be detecting overall emotional anxiety about speaking on the House floor, rather than emotions related to the topic of the speech. It is important to note that if women MCs are simply anxious about speaking in an overwhelmingly masculine institution, then they should exhibit higher anxiety than men regardless of speech topic, and may in turn speak with a higher baseline vocal pitch. But since our measure takes the legislator's baseline pitch into account, what we are capturing is deviations from this (potentially) already-heightened baseline. Additionally, a legislator's first speech in a given Congress does not exhibit meaningfully higher vocal pitch than other speeches. In Table S44, we find that the interaction between `Female` and `''Women'' Mentioned` is still positive and statistically significant when a dummy variable is included for the first speech. This suggests that our measure of emotional intensity is not simply picking up a general anxiety about speaking on the floor of Congress.

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Table S44: Female MCs More Likely to Talk About Women, with Greater Intensity (Controlling for the First Speech)

	Dependent variable:			
	Standardized Vocal Pitch		Standardized Vocal Pitch	
	(1)	(2)	(3)	(4)
Fixed Effects				
Constant	−0.002	0.151***	0.152***	0.152***
	(0.004)	(0.024)	(0.024)	(0.024)
Female	−0.017	−0.032***	−0.033***	−0.033***
	(0.011)	(0.011)	(0.011)	(0.011)
First Speech	0.033	−0.015	−0.036	−0.036
	(0.040)	(0.040)	(0.047)	(0.047)
"Women" Mentioned	0.020	−0.054***	−0.054***	−0.054***
	(0.014)	(0.014)	(0.015)	(0.015)
Female × "Women" Mentioned	0.090***	0.112***	0.110***	0.110***
	(0.027)	(0.027)	(0.027)	(0.027)
Female × First Speech			0.096	0.096
			(0.115)	(0.115)
"Women" Mentioned × First Speech			−0.035	−0.035
			(0.140)	(0.140)
Female × "Women" Mentioned × First Speech			0.277	0.277
			(0.286)	(0.286)
Additional Controls		✓	✓	✓
N_1	71,198	71,198	71,198	71,198
N_2	613	613	613	613
Log Likelihood	−100,722.000	−99,647.330	−99,648.740	−99,648.740
AIC	201,458.000	199,324.700	199,333.500	199,333.500

Note: Re-estimating Models 3 and 4 from Table 1 in the main text including a control for whether the speech was the first the MC delivered. Additional controls excluded to save space. Full models available upon request. `First Speech` is dummy variable which equals 1 when the speech is the MC's first in a given Congress. More details can be found on pages S84–S86. Levels of significance are reported as follows: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors are reported in parentheses.

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