Mad, sad, but mostly glad: how men and women in politics communicate using emotions in images

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Abstract

Political leaders use emotions to attract support from voters, take positions on issues or policies, and enhance communication. Yet men and women are constrained by gender role expectations, which limit the range and type of acceptable emotions that a leader can express. In this paper, we examine how gender shapes the political communication of emotion through a new measure: emotional expression in images posted by leaders on social media. We examine more than 450,000 Facebook posts by Members of Congress (MOCs), extracting images from these posts, faces from those images, and identifying MOCs faces out to identify when MOCs post images of themselves as angry, happy, or expressing any emotion at all. Specifically, we develop a custom facial recognition model to identify MOCs in their social media imagery and use a convolutional neural network to detect emotional displays. Drawing on research on role congruity, we argue (and find) that women MOCs will post more images of themselves being happy and expressing any emotion and fewer images of themselves as angry. We then use the source of these images (looking at the MOC herself versus other MOCs) to show that these differences originate in broader gendered patterns, rather than just personalization and self-presentation. The project offers an opportunity to understand how political leaders use emotions and images to communicate to constituents and how gender shapes these actions.

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Introduction

Political elites need to project the right image to the public (McGregor 2019). As a result, political leaders aim for their communication, from scripted ads to speeches to question-and-answer sessions to social media posts, to deliver a particular vision of the candidate (Kreiss, Lawrence and McGregor 2018, Dittmar 2015). The components of what the 'right' image includes are shaped by the electoral context, the nature and format of a particular message, and candidate characteristics.

One central dimension of how political leaders project the 'right' image is through images themselves and images *of* themselves. Candidates and elites are aware that images shape perceptions and behavior (Dittmar 2015, Kreiss, Lawrence and McGregor 2018) and engage in strategic actions to present images, particularly images of themselves, that will reinforce positives about the leaders and downplay negatives.

In this paper, we focus on how how gender shapes the political communication of public elites by constraining the presentation of emotions. Drawing on theories of personalization (McGregor 2018), emotional labor (Hochschild 1983), and gendered leadership style (Brescoll 2016), and role congruity (Bauer, Kalmoe and Russell 2022), we argue that gender constrains the emotions that men and women express in public (Bucy 2016, Masch 2020), which includes women expressing more happiness and men fewer emotions overall and more anger.

We examine a new source of data on how candidates present themselves: the expression of facial emotion in *images* in political communication. We draw from nearly 470,000 Facebook posts by Members of Congress (MOCs) to examine how political elites present themselves emotionally. Using combination of state-of-the-art computer assisted techniques, including facial recognition and automated emotional detection via machine learning to identify political leaders and classify their emotions, we identify happiness, anger, or emotional expression in images of MOCs in the database. We then connect these emotions to characteristics of the MOCs themselves, as well as the populations they represent.

We find strong evidence in favor of gender constraining how political elites engage in emotional displays in public. Women MOCs are much more likely to post images of themselves as happy and expressing emotion, even with controls for party, ideology, and district characteristics and less likely to post angry images. These results also hold for within party evaluations: both Democratic and Republican women's images of themselves are more happy and less likely to be emotionally neutral as compared to their in-party male colleagues.

To understand more about the underlying mechanisms, we then leverage the images and emotions that MOCs themselves post compared to images posted by other MOCs, showing that women are more happy and emotional *regardless* of which MOC posts those images. Our results contribute to scholarship on images as data (Torres and Cantú 2022, Aslett et al. 2020, Casas and Williams 2019), how political elites use social media (Russell 2021) to present their 'best face' to the public Carpinella et al. (2016), Bauer, Kalmoe and Russell (2022), and how gender constrains the behavior of political leaders. At the same time, our work presents a new mechanism of understanding candidate strategy, social media, and the use of images in politics.

Personalization, Emotions in Politics, and Social Media

Political leaders and candidates for political office engage in a wide set of communications to convince voters that they are worthy of political power. This communication often includes emotions, where leaders aim to express enough emotions as to not appear apathetic, but not too many emotions as to appear unreliable.

To examine how gender shapes how political elites use emotions in their political communication, we turn to images that members of Congress (MOCs) post of themselves on social media. For MOCs, political communication increasingly happen via social media, including Twitter, Facebook, and Instagram (Russell 2018, Straus et al. 2013). In social media posts, MOCs can signal their policy preferences outside the legislative process, cultivate reputations as experts on particular issues, and explain their Washington activities to a wide set of audiences (McGregor 2018). These posts are highly strategic, in content and timing (Kreiss, Lawrence and McGregor 2018). MOCs are the subject of a large number of their social media posts, framing their activities in ways that build connections and create context for constituents, donors, and other political elites (Schneider 2014, McGregor 2019)

While political activities on social media began when these sites were largely text-based (Evans, Cordova and Sipole 2014, Wagner, Gainous and Holman 2017), social media has evolved considerably. One central feature in this evolution is the increasing reliance on images and videos (Hand 2017). From increasing popularity of image- and video-based platforms (like Instagram, Snapchat, and TikTok) to a rising share of posts featuring images and videos on what were text-based platforms like Facebook, political messages on social media are now dominated by not just text from leaders, parties, and PACs, but also image-based communication. The *picture superiority effect* suggests that images in political contexts can provide a wealth of information (Mattan and Small 2021, Rosenberg et al. 1986).

Here, we focus on images posted by MOCs on social media as a means of understanding elite communication. As Druckman (2005) notes, "Images matter in politics." Visual information, including candidate appearances, voice tone, and non-verbal actions, shape how voters evaluate the fitness and ability of candidates (Carpinella and Johnson 2013, Carpinella et al. 2016, Everitt, Best and Gaudet 2016). Of particular importance in times of crisis, visuals can lead to voter learning in political contexts (Bucy and Grabe 2007, Bucy and Stewart 2018), especially if images promote emotional reactions (Gadarian 2014, Albertson and Gadarian 2014). A broad body of scholarship notes the importance of images in shaping reactions to elites (Bucy 2016, Boussalis and Coan 2021, Boussalis et al. 2021).

As social media activity from political elites has increased and media sources diversified, the personalization of these elite communications have also increased (McGregor 2018). Under the frame of personalization, political elites attempt to increase the public's sense of intimacy with them by providing more details about their personal lives and characteristics (Kreiss, Lawrence and McGregor 2018). Images, and emotional displays in those images on social media, are a key tool that political leaders use to engage in personalization (Metz, Kruikemeier and Lecheler 2020, Parry 2015).

Who can emote and when?

The characteristics of leaders, including political party, gender, race, and attractiveness, shape the "effectiveness of their nonverbal behavior" (Grabe and Bucy 2009, Fridkin et al. 2021, Boussalis et al. 2021, Masch and Gabriel 2020, Carpinella 2016 148). Voters generally associate political leadership with men and masculinity and women with feminine stereotypes (Bauer 2020, Bauer and Carpinella 2018, Holman, Merolla and Zechmeister 2021). Women in political roles thus must engage in work to demonstrate to voters that they possess the traits and issue competencies associated with political office (i.e., masculine ones) but also feminine enough to be considered a woman (Bauer and Santia 2021). This 'double-bind' challenges women seeking political power: they must be both masculine and feminine, but not too much of either one. These gendered expectations shape how women behave on the campaign trail and in political office (Bauer and Santia 2021, Dittmar 2015). Limits on emotions represent a central gendered dimension of expectations of candidate and elite behavior (Boussalis et al. 2021, Bauer 2015).

The expectations of emotions from political candidates emerge from broad gendered expectations about emotions in the general population. While men and women express emotions at similar rates, there are differences in *expectations* about women's and men's emotionality (Hess et al. 2010, Hutson-Comeaux and Kelly 2002). Beyond the overall level of emotional expression, specific emotions themselves are gendered, with women expected to express more happiness, and men anger. These have deep roots in childhood socialization, where girls are taught to express more happiness and emotions overall and boys more anger as early as preschool (Chaplin and Aldao 2013). As adults, men's anger and women's happiness are more accepted and expected, particularly in workplace settings (Sloan 2012).

Scholars refer to these emotional demands on women as "emotional labor" or a requirement that someone regulate their own emotions as a part of a job (Hochschild 1983). Akin to jobs that require physical labor (such as a construction worker), emotional labor is most common in care work (such as teaching), where people must present as possessing emotions (or not) that they do not actually feel. While both men and women can be held to the expectation that they provide emotional labor, gender role expectations and occupational gender segregation (Barnes, Beall and Holman 2021) mean that women bear the brunt of emotional labor. As a result of broad gendered expectations and emotional labor, "Despite the lack of empirical evidence for it, the notion that women are more emotional than men is prevalent in western cultures and the association of women with emotionality and of emotionality with the irrational has hindered women's opportunities in many types of work" (Sloan 2012 370).

We draw on the theory of emotional labor to argue that women in political office are expected to perform emotion at higher rates than their male peers. The social expectations of emotional labor mean that women need to appear to be emotional engaging and cannot appear too *unemotional*. We thus expect that:

> **Overall emotions hypothesis**: *Women in office will be more likely to present themselves as expressing emotions, compared to men in office.*

But not all emotions are equally acceptable. In additional to the overall level of emotional expression, leaders' emotions are constrained in their type: here we focus on anger and happiness as both have been documented to convey a dominant status to followers (Stewart, Waller and Schubert 2009). Leaders displaying anger project the ability to "neutralize external as well as internal threats to the group" (Boussalis and Coan 2021 p. 7). But leaders cannot simply be all domination all the time – they will be seen as psychopathic. So, leaders also need to express emotions like happiness that convey that they care and can interact with others (Sullivan and Masters 1988, Masch 2020). Thus, political elites want to express *anger* and *happiness* as well as a constrained range of overall emotions.[1].

The broader expectations about anger and happiness produce constraints on women's behavior in the general public, in specific jobs, and in leadership roles. In the general public, women are expected to be more happy and less angry: "The contemporary popularity of

[1]Leaders also want to shy away from any emotion than conveys weakness, including sadness, nervousness, or fear. Studies of emotional expression in political contexts find almost no expression of 'weak' emotions among political candidates or leaders (Masters et al. 1987, Bucy and Grabe 2008, Boussalis and Coan 2021, Boussalis et al. 2021)

the phrase 'resting bitch face' reflects expectations on women in the public sphere to perform happiness and 'just smile', as many women are encouraged to do by (typically men) strangers, acquaintances, and loved ones, on the street, at home, and at work" (Jackson 2019 p. 696). In occupations with emotional work, workers (especially women) must express more positive emotional engagement (Ahmed 2010, Jackson 2019) and avoid negative emotional engagement. Research of women as leaders echo these expectations: Brescoll (2016) and Bauer and Taylor (2022) argues that gender emotional stereotypes lead to a double-bind for how women in leadership roles present themselves visually to the public. On one hand, women need to avoid representing emotions like anger that are associated with masculinity as may remind voters that these women are, in essence, women (Bauer 2019). But women also want to appear to have competencies in femininity as without it, they may be seen as "failing to fulfill their warm, communal role as women" (Brescoll 2016 415). One way that women demonstrate that they fulfill feminine roles is by engage in happiness, particularly in public spaces. Happiness is a natural choice for women in political office because, as Boussalis et al. (2021) argue, it is both an acceptable emotion for political leaders *and* for women more generally, thus bypassing the double-bind.

> **Anger hypothesis**: *Women in office will be more likely to present themselves as angry than will men.*

> **Happiness hypothesis**: *Women in office will be more likely to present themselves as happy than will men.*

We also have the ability to examine the role that strategic self-presentation versus more general socialization and leadership behavior plays in the patterns of which emotions appear in images of MOCs by examining whether a particular image is posted via the account of the Member of the Congress or by an account of another MOC.

We use the source of the images of MOCs to test two alternative possibilities for the mechanism behind gender differences in MOCs' emotional expression. First, women may be socialized to express (and trained as they seek political power) more emotions, especially more happiness, and fewer masculine emotions like anger. In this setting, we would observe images of women MOCs as more emotive and happy and less angry *regardless of who posted the image.* A second possibility is that emotions emerge entirely out of women's efforts at personalization and emotional labor. In this scenario, we would expect that gendered patterns in emotional expression would be observed *primarily in the images that the MOCs posts of themselves.*

Emotions in images

To understand how gender shapes how MOCs use emotions political communication, we need a large set of images that feature the MOCs from sources that the leaders themselves control. To access this, we turn to social media and collect all images from MOC Facebook accounts. We focus on the 116th Congress and collected posts from November 2019 to the inauguration of President Joe Biden in January 2021. To do so, we first assembled a list of all Facebook handles for the MOCs in session at any point during this time period, resulting in 1502 accounts representing 575 MOCs.[2]. Many MOCs maintain more than one account so we started with official accounts and then collected (via a websearch for each MOC) a more complete list, available here. We then used the CrowdTangle API to collect all posts from these accounts. Overall, across the accounts, we collected 469,953 Facebook posts.

To assess emotional self-presentation on social media, we need to be able to extract emotions from this very large corpus. Scholars of political communication have long been interested in obtaining information about emotional expression from images, videos, and sound (Dietrich, Enos and Sen 2019, Druckman 2003, Sullivan and Masters 1988), but have encountered a variety of hurdles associated with the cost and time required to manually code and analyze these media at large scales. For example, the Facial Action Coding System, a widely used coding scheme, takes 10 minutes to analyze a single image or frame from a video (Ekman and Friesen 2003) to identify the emotional expression from a face in an image

[2]Our numbers exceed the total number of members as we include any individuals in office any point during the time period, including those who only served for a short period of time

(Stewart, Salter and Mehu 2011). Our dataset includes 76,974 images of MOCs, making the time and cost associated with applying these methods out of reach.[3] The use of computer vision also distinguishes our work from prior research on images in campaign contribution, which largely relies on manual coding, thus limiting the number of items evaluated.[4]

Fortunately, we are able to turn to machine learning as a tool for extracting emotional expressions. To do so, we turn to computational methods that use images as data (Torres and Cantú 2022, Casas and Williams 2019), drawing directly from work that has analyzed facial expressions of political leaders (Boussalis and Coan 2021, Boussalis et al. 2021, Joo, Bucy and Seidel 2019).

Below we outline the steps we took to extract measures of facial displays of MOCs in images of themselves that they posted onto their Facebook accounts over the sample period. The pipeline includes three main steps: (1) use a deep learning model to *detect* faces in all collected images; (2) employ a transfer learning approach to *recognize* the identity of a given face and determine whether it matches the MOC from whose account it was collected; and, lastly, (3) measure the *facial display of emotion* in each classified MOC face image using the Microsoft Azure Face API. In the last sections, we describe the remaining variables in our dataset and the statistical methods used to test our hypotheses.

Face detection

While there are a number of approaches to face detection (or face "alignment") described in the literature (Zafeiriou, Zhang and Zhang 2015), we examine two deep learning-based approaches that have been shown to give state-of-the-art performance across a wide range of face detection tasks: the Multi-task Cascaded Convolutional Neural Network (MTCNN) introduced in Xiang and Zhu (2017) and the RetinaFace model described in Deng et al.

[3]For example, applying the Facial Action Coding System to these images would take (conservatively) 12,000 hours to code.

[4]For example, Mattan and Small (2021) evaluates a large number of photographs by hand and covers a total of 685 photos and Metz, Kruikemeier and Lecheler (2020) examines 435 images in their study of personalization in images.

(2020).[5] Though MTCNN and RetinaFace are more computationally expensive than traditional approaches, they have been shown to perform well on "difficult" to detect faces (e.g., profiles, lighting, etc.). From the nearly 470,000 Facebook posts, we detect over 385,000 faces.

Recognizing MOC faces

Next, we employ a set of supervised and semi-supervised algorithms to select the faces of MOCs from the set of detected faces. To accomplish this, we compare each face from our large set of unknown face images to a much smaller "comparison set" of clusters of verified MOC face images. For each comparison, we determine the Euclidean distance between the unknown and verified face images, and use a threshold rule to determine a match.

First, we needed a way of easily generating a diverse set of face examples for each MOC that would populate our "comparison set." To do this, we first encoded the detected faces using the Inception Resnet model which is pretrained on CASIA-WebFace and VGGFace2 datasets. This represents each cropped face image in our dataset as a vector of floats. Next, for each MOC in our study, we use these image embeddings and an unsupervised clustering algorithm to generate an MOC-specific cluster of faces which can be used when performing the eventual lookup task for all extracted faces in our corpus.[6] The clustering procedure returns a few clusters for each MOC account, with the largest cluster typically being other people and the second largest cluster typically being that of the MOC in question. A research assistant went through each cluster for each MOC and determined the cluster that corresponds to the MOC. A set of approximately 15 "verified" images from a matched MOC cluster is then included in the "comparison" set of embedded images.

The next phase of the facial recognition pipeline is the actual classification of faces. Here,

[5] To align faces using MTCNN, we utilize the PyTorch offered in the `facenet-pytorch` library; for RetinaFace, we use the PyTorch offered in the `retinaface-pytorch` library

[6] While there are a number of approaches that could have been used, including k-means clustering, we decided to use the DBSCAN algorithm from the `scikit-learn` package in Python. This method performs quite well when working with unbalanced clusters, as is the case with our data where some MOC faces have many examples (e.g. Nancy Pelosi), others have some examples, while most faces in our dataset should not be clustered because they are not faces of an MOC.

we determine whether a given face image belongs to a certain MOC based on an evaluation of the Euclidean distance of the image embeddings of the pair of images. For each face in our corpus, we find the MOC cluster in our "comparison" set of which it has the smallest Euclidean distance. We next evaluate whether this Euclidean distance is meaningfully small by comparing it to a determined threshold level t:

if min distance $< t$ **then**

  Classify as relevant MOC

else

  Classify as not an MOC

This step is crucial, as we wish to avoid naively classifying MOC faces purely based on the minimum Euclidean distance. We define the constant t by calculating pair-wise Euclidean distances for all images in the "comparison dataset". Distance values are then separated into two distributions, one for within-person and the other between-persons. We then set the value for the threshold t as 2 standard deviations above the mean for the within-person distribution (which follows a normal distribution). Using the above pipeline, we identify 76,974 MOC faces in our corpus.

Measuring MOC facial displays of emotion

Given the theoretical expectations discussed in Section , our analysis focuses on facial displays of either *happiness* or *anger* as well as the expression of *any emotion*. We use the Microsoft Azure Cognitive Services' Face API to extract facial displays of emotion. The Face API recognizes human faces and predicts the level of eight emotions: anger, happiness, contempt, disgust, fear, neutral, sadness and surprise. While the underlying architecture is closed-source, this software likely relies on deep-learning convolutional neural networks (LeCun, Bengio and Hinton 2015, Krizhevsky, Sutskever and Hinton 2012) trained on data annotated using the Ekman and Friesen (2003) model of discrete facial expressions (Bargal et al. 2016). For each MOC image, the API returns a confidence score for the eight emotions mentioned above, ranging over the interval $[0, 1]$, with all emotion confidence scores for a given image summing to one. From the MOC faces we passed to the Face API, the program is able to encode emotions in facial displays of 49,145 of the images.[7] Because we are interested in how MOCs engage in *self* presentation, we first focus on the 28,338 images that the MOC posted of themselves (not, for example, images of a MOC that appear on another MOCs account). We also examine a broader set of images (202,678) that are images of the MOC posted by any MOC in our dataset, including the MOC themselves.

Dependent and Independent Variables

In order to test our hypotheses, we estimate a series of statistical models, where the unit of analysis is a self-posted MOC face image. The models include the following dependent variables: confidence scores for (1) happiness, (2) anger, and (3) non-neutral facial displays. For each, the value is represented as a z-score, where 0 represents the mean sample emotion value.

Our main explanatory variables are a binary measure of whether the MOC is a man or a woman and the political party identity of the MOC.[8] Our dataset includes 26% women ($n = 151$) and 74% men ($n = 424$), and nearly even numbers of Democrats ($n = 285$) and Republicans ($n = 287$).

We also control for a variety of factors that might influence whether and when a MOC posts images of themselves expressing emotions, including their race, age, chamber, ideology,[9] pro-Trump voting record, the MOCs' margin of victory in the last election, and district/state partisanship, measured as the proportion of the 2016 two-party vote won by Hilary Clinton (Amlani and Algara 2021). We also include a control for the median income of the district

[7]The API is unable to determine emotions in 17,422 of the images because the original image is too small.

[8]Given the very low number of independents in the U.S. Congress during our period of inquiry, we focus on differences between Democrats and Republicans.

[9]We use the two dimensions from the NOMINATE scores: Nokken-Poole 1, which represents the general economic left-right position of MOCs, based on their voting behavior in a particular Congressional session and Nokken-Poole 2, which is a broader catch-all measure of ideology (Boche et al. 2018, Nokken and Poole 2004).

Emotion	Women (%)	Women (n)	Men (%)	Men (n)
anger	0.25	36	0.15	42
contempt	0.08	11	0.05	15
disgust	0.01	2	0	0
fear	0.03	5	0	1
happiness	83.22	12,186	76.11	20,846
neutral	15.16	2,220	23.12	6,333
sadness	0.71	104	0.37	100
surprise	0.54	79	0.19	52

Table 1: This table displays relative frequencies and counts of images by modal predicted emotive display and gender.

and state in the analyses from the 2019 ACS. All variables are measured at the appropriate geographic level, i.e., median income and Clinton vote are measured at the district level of members of the House and at the state level of members of the Senate. Finally, we include the number of followers a given MOC has on all their social media accounts.[10] All continuous variables are rescaled as z-scores to ease in comparing the substantive effects for coefficients.

Modeling strategy

We estimate separate models predicting whether any photo that a MOC posts of themselves will present as happy, angry, or non-emotional (neutral). Specifically, we run a series of linear mixed-effects models where random intercept-effects are included for each MOC and the standardized measure of emotion is the dependent variable.

Results

We start by looking at the difference in self-presentation of emotional expression by men and women with our full set of controls. We present the results as a coefficient plot with full controls in Figure 1. Recall that we expected that women (men) would be more (less) likely to present themselves as happy and less (more) likely to present themselves as angry or as non-emotional. We find strong support for our *happiness* and *emotionality* hypotheses

[10] This includes the number of followers on Facebook, Twitter, and Instagram.

and weak support for our *anger* hypothesis. The substantive effects for gender are far larger than any other variable in our model, including partisanship. Indeed, across our predicting emotions in the MOCs faces, gender is the only consistently significant predictor. We do see some emotion-specific patterns: more conservative legislators (on dimension 2) post more neutral images, Senators are less happy and more neutral, and more followers is associated with more anger. But nothing in our models compares to the effects of gender, in significance or substantive effects.

We also see that the African American legislators in our sample present as expressing less happiness and emotion and more anger. We take these results with a great degree of caution: a broad body of scholarship has documented racial biases in both facial recognition and emotion detection classifications (Xu et al. 2020) and the flaws in the broader racism of these platforms (McMillan Cottom 2020). It is entirely possible that there are intersectional expectations for emotional expression across gender and race (Ghavami and Peplau 2013), but it also possible that either of the two classification processes that we use have systematic biases that produce these results.

Gender representation in the United States is highly partisan, with women far more likely to be Democrats and men more likely to be Republicans (Ondercin 2017). Women's representation in the parties (Ondercin 2022), issue ownership by the parties (Holman and Kalmoe 2021*b*), and rhetoric from party leaders (Holman and Kalmoe 2021*a*, Cassese and Holman 2019) have created and reinforced an environment where the parties themselves are also gendered (Cassese and Holman 2018, Winter 2010). In this context, it is possible to imagine a world where the relationship between MOC gender and their emotional self expression is deeply shaped by partisanship, with Democratic women pressured even more to act 'feminine', including in emotional expression. We examine this possibility by estimating models separately for Democrats and Republicans.

Broadly, gender effects are not confined to either party: both Democratic (left pane) and Republican (right pane) women are more likely to present themselves as happy and less likely to present a neutral face. The only place where we observe differences is with anger:

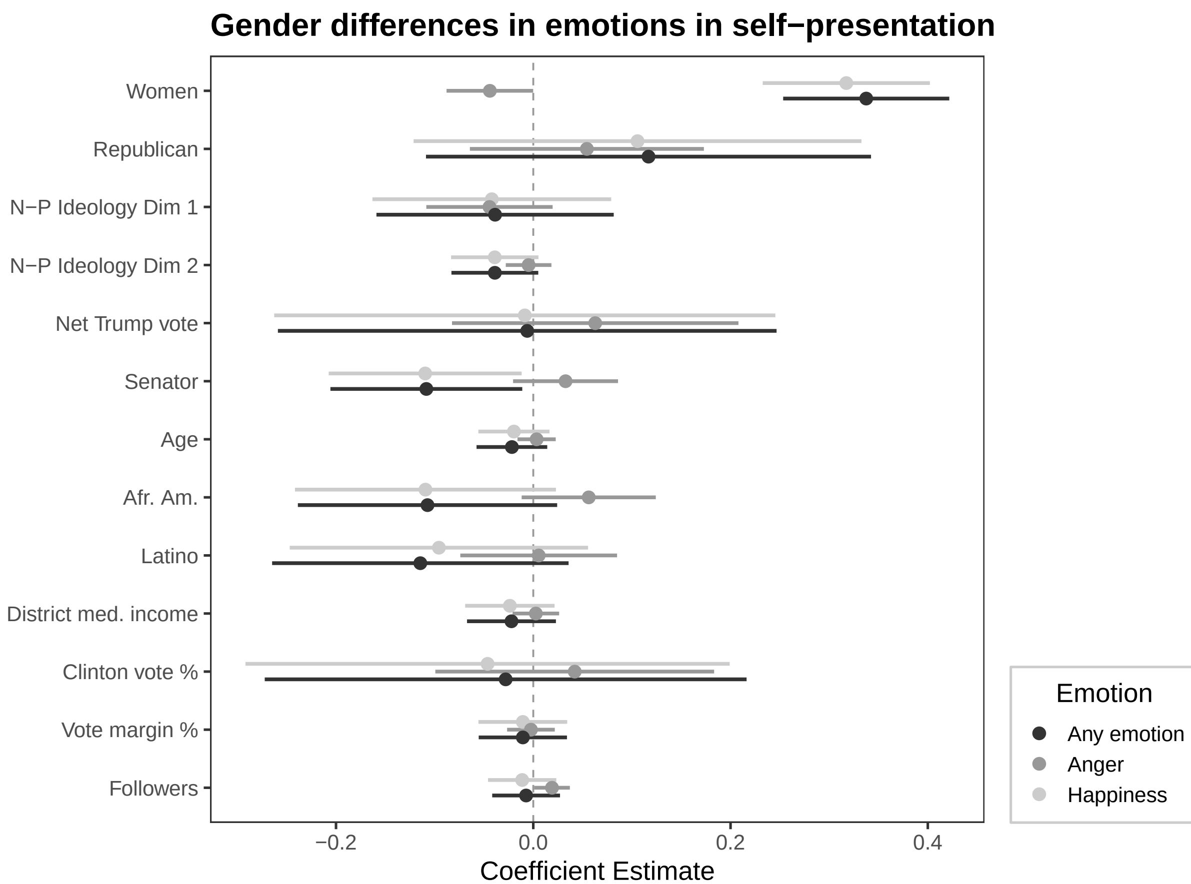

Figure 1: Probability that any picture that an MOC posts of themselves presents the MOC expressing happiness (light gray), anger (gray) or no emotion (dark grey). Dots are coefficients, bars standard errors.

women in the Democratic Party are less likely to present themselves as angry as compared to their co-partisan men, while there are no gender differences in anger presentation among Republicans. Again, gender in both models is the most consistently significant predictor and has the largest substantive effect.

Next, we use the source of the image to test if these patterns are due to purely presentationalism or are these broader gendered patterns? We use the *source* of MOC images to examine this difference. Recall, if the emotional differences we observe are entirely due to presentationalism, we should only expect to see those differences in images the MOC posts of themselves. But if these differences are due to patterns of expected behavior for men and women broadly in society and in leadership positions specifically, we would expect to see gender differences across all images of the MOCs, regardless of who posts the images.

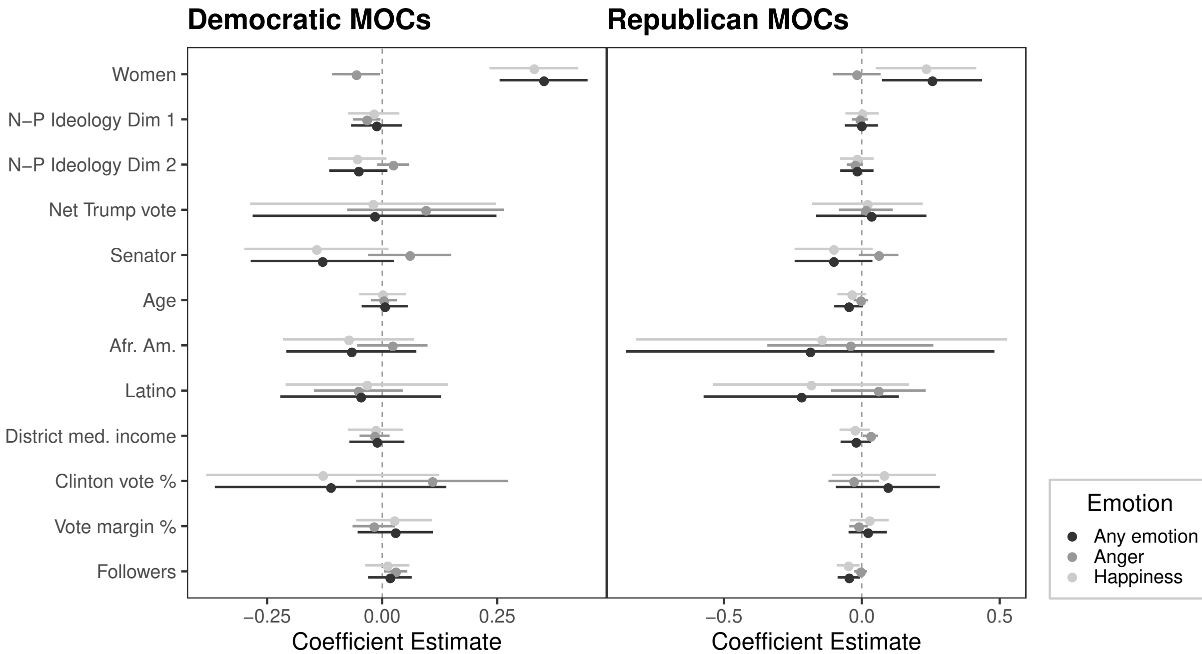

Figure 2: Probability that any picture that an MOC posts of themselves presents the MOC expressing happiness (light gray), anger (gray) or no emotion (dark grey). Republicans on the left, Democrats on the right.

To examine this difference, we use the same model, but a larger population of images: any image of any MOC in the dataset from all MOC accounts. We include three new controls in the model: whether the image is from the MOC's own account (*self-post*), and interaction between that value and whether it is a woman leader, and whether the image comes from a MOC's *same party*.[11]

Even when we control for who posts the image of the MOC, we see broad patterns of gender differences, with women's images expressing more emotion overall and more happiness, although anger loses significance in these models. We see similar patterns in images that the MOC posts of themselves, but no difference when we examine the interaction between gender and MOC's own posts. We interpret these findings to support a view that the gendered patterns in emotional expression we identify are due to broader expectations for women and leaders and not just due to personalization in the images that MOCs post of themselves.

[11]One possibility is that MOCs from another party post images that they believe are purposefully harmful to a member of Congress, such as images that present the leader expressing sadness or fear.

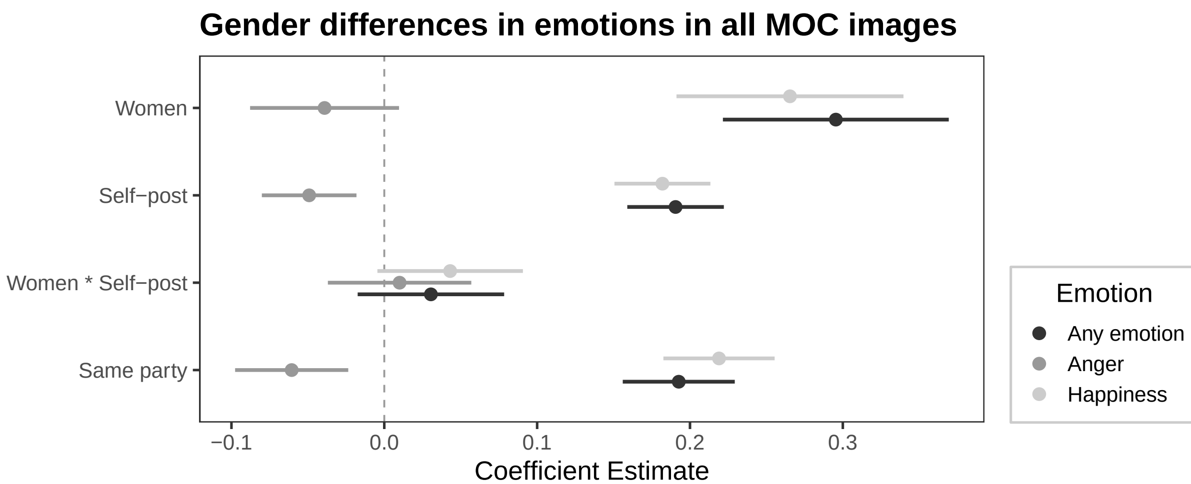

Figure 3: Probability that any picture of an MOC includies the MOC expressing happiness (light gray), anger (gray) or no emotion (dark grey). Dots are coefficients, bars standard errors. Note that covariate estimates are not displayed in this figure.

Discussion

Political elites are interested in presented their "best face" to the public, including in actual images of themselves. Research on campaign strategy notes that candidates for Congress and MOCs – and elites in other countries – work strategically to present a particular image to the public (Kern and Just 1995, Lalancette and Raynauld 2019, Schneider 2014). Here, we focus on the emotions that political elites portray in images of themselves on Facebook. The emotions in these images are overwhelmingly positive, with happiness the most common emotion by far and with women posting even more 'happy selfies' on Facebook. These results suggest a departure from other research on Congressional communication on Facebook, which analyzes text and finds that negativity and anger dominate posts (Hua and MacDonald 2002, Evans, Gervais and Russell 2022)

Social media presents an interesting case for studying political communication as the MOCs are not entirely sure of what the audience for any post might be. Scott (2022) finds, for example, that US presidential candidates express more positive emotions in their speech at events where the audience are all followers and more negative emotions at events where audience members need to persuaded to support the leader. The probability that a broader audience will see and scrutinize a leader's behavior might also play a role, with leaders limiting their emotions as the audience expands. Our findings of differences across House and Senate members and that the size of a MOCs follower base shapes their emotions echo that the audience matters in how MOCs present themselves.

While candidates can control what images are posted on their social media feeds, they have significantly less control over what happens to those images after posting. The presence of women as candidates also shapes how the media covers races and politics (Dunaway et al. 2013, Bauer 2022, Bauer and Taylor 2022), including increasing the probability that the media will focus on traits (like emotional control) over issues. In newspaper photographs, women are more likely featured with happy expressions (Rodgers, Kenix and Thorson 2007). This suggests that these messages from MOCs may be amplified by the press, further emphasizing the need for women in political office to control their own behavior.

We approach the study of emotions in politics from a new theoretical perspective: that there is emotional labor (Hochschild 1983) required as part of the job of holding office and that more emotional labor is expected from women than from men, particularly in the expression of positive emotions. We find robust evidence in support of this understanding of how political elites present themselves to the public. In many ways, examining the images that MOCs post of themselves on social media represents the best case for understanding how MOCs *want* the public to see them. Our results suggest that MOCs, particularly women, want the public to see happy people.

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Supplementary Materials

Contents

Appendix A Collecting social media accounts of MOCs

For each individual who represented any of the fifty states in Congress at any point during the 116th Congress, we used a combination of existing lists of social media accounts and web searches to identify all accounts held by the MOC. This represents a far larger set of accounts than is typically used in social media research on Congress as we did not just rely on their Congressional accounts but also collected their campaign accounts across the two platforms. This resulted in a total of 2,066 accounts or 4.07 accounts per MOC; the full list of accounts is available on (Github redacted for peer review). Every MOC had at least one social media account in our dataset.