

Picturing Representation

The Electoral Logic of Congressional Self-Presentation

Pamela Ban*

Benjamin S. Noble[†]

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Abstract

Congressional politics has nationalized. Past research focuses on how this trend shapes legislative rhetoric, but we argue that it also shapes presentation of self: lawmakers' incentives to present themselves as people constituents should know and trust. We theorize that members in aligned constituencies, whose voters share the party's commitments, display national figures as surrogates carrying those commitments in their stead; marginal members, who must cultivate a personal vote beyond party labels, present themselves. We construct a new corpus of 2.2M Twitter images shared by 803 members of Congress (2017-2023) and use facial recognition to identify every lawmaker and a set of salient national figures in them. We show that the most marginal members appear in 12 percentage points more of their images than the most aligned. In aligned feeds, the share of co-partisan national surrogates triples. Nationalization affects more than rhetoric: it shapes who lawmakers put forward as the representative.

*Associate Professor, Department of Political Science, University of California, San Diego, <https://www.pamelaban.com/>, pmban@ucsd.edu.

[†]Assistant Professor, Department of Political Science, University of California, San Diego, benjamin noble.org, b2noble@ucsd.edu.

A large body of research holds that congressional elections have nationalized. Voters increasingly judge members of Congress through the president and the parties, split-ticket voting has declined, and the electoral premium incumbents once earned from a personal following appears to have shrunk (Hopkins 2018; Jacobson 2015; Abramowitz and Webster 2016; Carson, Sievert and Williamson 2023; Sievert and McKee 2019), raising concerns about accountability. Members, for their part, have followed their voters; they present their work more in national than local terms (Lee 2016; Grimmer 2013a; Noble 2024; Ban and Kaslovsky 2025; Russell 2021). We know, in short, that members increasingly talk about national politics. However, nationalization may shape the representative relationship beyond what lawmakers say—extending to *whom* lawmakers put before constituents as the representative. Here, we ask when members present themselves as the representative and when they put national figures in their place.

Members of Congress do more than describe their work to constituents. They also present themselves as people constituents can know and trust. This presentation of self is what Fenno (1978) gave the greatest weight in his account of home style: members placing themselves before those they represent, so that constituents can judge their qualification, identification, and empathy, and come to know and trust the person. Nationalization would seem to put this at risk, since it rewards attention to national politics over the candidate-specific factors on which a personal vote rests. If members give more of the frame to the party, then the person constituents are asked to trust and see as responsible for their representation is less the member and more the national figures of the party she speaks for. Whether that happens, and for which members, is what we set out to answer.

This question has gone unanswered because prior work has largely focused on legislative communication that observes what members say. However, members now conduct much of the presentation of self through the images they post, and an image records a choice that text cannot: whom members choose to show. A message about a local hospital reads the same whether it comes with a photograph of the member among the hospital's

nurses or a photograph of the president visiting it, and those two images place different people before constituents as the one doing the representing. Previous work has used images as data (e.g., Torres 2024; Webb Williams, Casas and Wilkerson 2020) and begun to measure home style from images, showing that whom a member poses with signals identification and empathy to constituents (Anastasopoulos et al. 2024; Xi et al. 2020). We ask the question that comes before that one, whether the member presents herself at all.

When members do not appear, whom do they put before constituents? Mansbridge (2003) showed that representation need not run through the representative elected to a given seat, that constituents may find representation in legislators elsewhere who share their commitments, which she calls surrogate representation. Previous work has asked who serves as a surrogate or how constituents come to find one (English, Pearson and Strolovitch 2019; Mansbridge 2011). Here, we examine a related supply side dynamic: the member herself putting a national leader of her party (e.g., the president) before constituents in her place. We interpret the pattern of images in which a co-partisan national figure appears and the member does not as national surrogacy: the member presenting her party's figures as the face of the cause her constituents presumably share.

Why would a member make themselves a smaller part of what their constituents see? The study of Congress assumes members want to be known and that a member's reputation with her constituents is her main electoral asset (Fenno 1978; Mayhew 1974). We argue that the answer lies in what a member's constituency rewards, which for some members, is not their personal visibility. In a constituency where the member's own partisans dominate—an aligned constituency—the member's support rests on commitments her constituents already share with her party (Grimmer 2013a). That cause can be carried by her party's national figures who can convey it more legibly than the member given their salience and strong association with these partisan commitments. In a constituency that is competitive or dominated by the other party—a marginal constituency—the member needs voters who may not share her party's commitments. In this case, the member

cannot win those voters with her party's reputation. She must win them with her own reputation by building a personal vote that survives her constituents' opposition or ambivalence to her party (Cain, Ferejohn and Fiorina 1987). National surrogates cannot build that reputation for the member serving a marginal constituency because the voters that member needs do not share the cause the surrogate stands for. The member, appearing for herself, can. Members with a relatively more aligned constituency should therefore occupy a smaller share of their feeds and put forward their party's national figures more, compared to members with a relatively more marginal constituency, who should occupy a larger share. In short, aligned members dilute their own presence with their party's surrogates, while marginal members curate feeds in which they remain the representatives their constituents see.

We test our argument with a new dataset of roughly 2.2 million images posted on Twitter by 803 House and Senate members between 2017 and 2023. We first identify whether the posting member appears in each image using a human-validated facial recognition pipeline. We match all detected faces in our image corpus against lawmakers' official portraits, and we follow a similar process to identify the president and other salient national figures, separating these into co-partisan camps. The basic fact that emerges is a gap: members in the least aligned fifth of constituencies appear in 44 percent of their images, members in the most aligned fifth in 32 percent. We find that an 11-point increase in co-partisan presidential vote share is associated with a 3.6-point decline in the share of a member's images that show her, about 25 images over a Congress for a member posting 697 images per Congress. This effect survives controls for chamber, party, seniority, leadership, demographics, and past vote share. Because the argument is about what members strategically choose to show, we probe several alternative explanations: our results are not fully explained by a focus on different topics, different scheduling choices, or different resource allocations across marginal and aligned members. Given our limited time series, we are not able to determine whether this behavior is driven by selection or

adaptation, however, the electoral logic predicts the same pattern in either case. Our main findings are accordingly about the association between alignment and presentation.

The gap tells us that the aligned member occupies less of her feed, but what occupies the rest of it? We first test our theorized explanation: images of co-partisan national figures, which we interpret as surrogate representatives. These images bear a strong relationship to constituency alignment, and they account for about one-fifth of the 12-point gap—a disproportionate contribution for a category that makes up only about two percent of the corpus. Their share roughly triples across the alignment range, which makes them the category most responsive to alignment. However, surrogate images, while significant, provide only a partial explanation of what stands in the aligned member’s place. We decompose the gap into several other categories including salient opposition figures posted as foils, other less salient lawmakers, unidentified faces, and the largest contributor to the gap, text-based graphics with no face depicted. Some of these image types are consistent with other nationalization-based predictions (e.g., out-party foils, as in Noble 2024), and none offer constituents an image of a representative serving them. Where the member’s party dominates, she is more likely to cede the frame to other kinds of messaging. Finally, we provide evidence that this presence gap matters. Using data from the CES, we show that members who more frequently appear in their feeds are more likely to be recognized by their constituents. The relationship is not causal, but it provides modest evidence of a link between self-presentation and recognition, a precursor to the cultivation of a personal vote.

These findings speak to four literatures. First, research on representation has, since Mansbridge (2003), recognized that constituents may find representation in surrogates. We show that members themselves supply surrogates to their constituents, and we identify when they do. Second, research on nationalization has measured what members say and how voters vote (e.g., Ban and Kaslovsky 2025; Carson, Sievert and Williamson 2023; Hopkins 2018; Noble 2024). We show that the same electoral line divides whom

members put forward as the representative, and we show that aligned members not only nationalize what they say but whom constituents see. Third, research on home style has, since Fenno (1978), lacked a systematic measure of the component he placed at its center: the presentation of self through which constituents judge qualification, identification, and empathy. We provide one for the full membership of Congress and explain, through the logic of the personal vote (Cain, Ferejohn and Fiorina 1987; Mayhew 1974), why constituency alignment should shape it. Fourth, research on political images has shown that images carry information text does not (e.g., Torres 2024; Webb Williams, Casas and Wilkerson 2020), and that constituents read who appears in a member's images as a signal (Anastasopoulos et al. 2024; Xi et al. 2020). We examine one basic feature of an image, whose face is in it, and show that it reflects what members choose to present. Overall, our findings show that nationalization extends beyond rhetorical self-presentation and affects who members place before constituents. Where the party's voters dominate, the representative still appears—but her constituents see less of her and more of her party's national figures.

Whom Members Present as the Representative

Representation is a relationship between a legislator and those she represents, and as Fenno (1978) observed, legislators do not simply hold this relationship but present it to their constituents. Fenno (1978) described that the presentation of self as the component of home style that members cared about most. By placing themselves before constituents, members allow constituents to judge their qualification, identification, and empathy, and through these judgments, come to trust them. This trust is what allows constituents to evaluate a member as a person rather than as a party label, and it is the foundation of the personal vote: the portion of a member's support that is attributable to her own record and reputation rather than to her party (Cain, Ferejohn and Fiorina 1987). A personal

vote, however, requires that constituents first know who the member is, since they cannot form the impressions that produce trust without having encountered her. Presentation of self is the means by which members provide that encounter, and in this sense it is where the cultivation of a personal vote begins.

Fenno (1978) documented the presentation of self by accompanying members through their districts, and subsequent research has largely studied representational style through what members say rather than how they present themselves (e.g., Grimmer 2013*b*; Ban and Kaslovsky 2025; Noble 2024). We move beyond what members say to who members show in the images they share—where presentation of self and its alternatives are observable. Here, members may show themselves, someone else, or no one at all.

If members do not show themselves, who do they show? In a nationalized congress, the party's national figures, who are better known and more associated with the party's core commitments, offer one potential alternative. Our questions are whether members vary across this dimension of self-presentation, which members do so, and under what electoral conditions. We first conceptualize presentation of self and its alternatives; then, we develop the electoral logic behind those choices.

Conceptualizing Presentation and Its Alternatives

How can a member present the representative relationship to her constituents? We conceptualize three possibilities, focusing on images as one important place where these choices are legible. Naturally, a member can present herself, as Fenno (1978) described. However, we conceive of two alternatives: a member can present someone else in her place or a member can share a message with no representative figure at all. Images let us observe not only when a member steps out of the frame but who, or what, she puts there instead. We note that each of these possibilities describes a single image. Across a feed, our main argument concerns the share of images in which a member appears.

First, we consider *self-presentation*. A member presents herself whenever she appears

in an image, whether alone or among others, and whether or not she is the central figure. For example, a member posting a photo where she is at the edge of a group of veterans has placed herself before viewers in the same way as a member appearing alone at a podium or next to the president. In the last example, the president is part of how the member presents herself, not a substitute for her presence. This conceptualization of member presence in an image follows the account of presentation of self in Fenno (1978), which turns on constituents *seeing* the member and forming impressions of her, and not on whether the member occupies the center of the frame.

When the member does not present herself in the image, who or what is put forward in her place? Our primary alternative explanation is a co-partisan national figure. A member who posts a portrait of her party's president, for example, may intend to praise him, to signal her shared ideological or political commitments, or to let him speak for her. Whatever the member's intent, we observe that the member has placed a figure of her party in place of herself.

What does this placement imply for representation? Existing work provides evidence that who appears in a member's images shapes how constituents evaluate her (Anastasopoulos et al. 2024). On that basis, we interpret the recurring presence of co-partisan national figures in a member's feed, where she herself is absent, as a form of *surrogate representation*: the member directs her constituents to look to someone other than herself as the person standing in for her and carrying their shared cause. Our interpretation builds on Mansbridge (2003), who defines surrogate representation as representation by a legislator with whom the constituent has no electoral relationship.¹ We extend this concept to focus broadly on co-partisan national figures whom a constituent would likely recognize as carrying the party's cause: those whose standing is established independent of the member's feed, like the president or congressional leaders.

¹Our concept differs from Mansbridge (2003) in that some national figures, most obviously the president, are figures constituents do vote for at other levels of government or other offices. However, the two share the feature that matters for our purposes: none of these figures is the representative elected to that seat.

Members can also post images that show neither themselves nor a surrogate, such as other lawmakers, ordinary people, or no one at all. Our argument concerns the choice between presenting oneself and presenting a party figure, so we set these aside here and return to them when we decompose the member-presence gap below. Taken together, these categories allow us to characterize a member's feed in terms of how much of it she devotes to herself and how much she devotes to alternatives. Because a feed is finite, each image falls into one of these categories and not another. A member who devotes more of her feed to surrogates or other content has, to that extent, devoted less of it to herself. We argue next that the balance a member strikes across these categories is driven by electoral incentives.

The Electoral Logic of Whom Members Show

Under which conditions can we expect a member to present herself? We argue that the answer lies in what a member's constituency rewards, and we characterize constituencies in terms of their alignment with the member. Following Grimmer (2013a), we consider a constituency to be aligned when two conditions hold. First, one party's voters must dominate the constituency. In a polarized era, partisans within a party broadly share a coherent set of policy commitments, so when one party's voters dominate a constituency, there is a cause that a legislator can credibly speak for. Second, the member must belong to that party. A Democratic senator in a heavily Republican state satisfies the first condition but not the second; the electorate coheres around a cause, but it is not hers. We refer to constituencies that satisfy both conditions as aligned and all others as marginal. We note that this distinction is not the same as constituency homogeneity. A homogeneous constituency with an out-party incumbent, such as Senator Joe Manchin in West Virginia, is marginal in our definition, because such a member faces the same problem as a member in a competitive same-party seat: she needs the votes of people who do not share her party's commitments. We acknowledge that this definition groups together two kinds of

marginality, the competitive seat and the out-party seat, that may differ in other respects. Our theory treats both as marginal because both require the member to win voters her party label cannot deliver.

In an aligned constituency, the member's support rests on political commitments that her constituents already share with her party, and those commitments do not depend on who carries them. The reason lies in how partisan voters process political information: they rely heavily on partisan cues to evaluate candidates, and the party label does much of the work (Druckman, Peterson and Slothuus 2013; Popkin 1991; Rahn 1993). Among co-partisans, evaluations of a member track evaluations of the president and the party's national standing, so that the president's approval functions as a heuristic for judging the member herself (Jacobson 2019; Gronke, Koch and Wilson 2003). For such voters, the party's national figures give the cause a concrete form: the president or a salient party leader, like Bernie Sanders, is recognized as the face of what the party stands for in a way that a rank-and-file member is not, and an image of him conveys the shared commitment more legibly than an image of her. For a member in an aligned constituency, then, her own presence may add relatively little to what her coalition already sees in these figures, who are more efficient cues than the member herself. As a result, such a member may give more of her feed to the party's figures at little electoral cost and greater benefit than her own presence would bring. This expectation parallels a pattern documented in text, in which members from more aligned constituencies describe their work in national rather than local terms (Ban and Kaslovsky 2025; Grimmer 2013a). We extend that logic from what members say to whom they show.

In a marginal constituency, by contrast, the member needs the votes of people who do not share her party's commitments and who will not vote for her on the basis of its label. Existing work on the personal vote provides the basis for our expectation here: legislators in such circumstances cultivate support through a reputation of their own, one that survives their constituents' opposition or indifference to the party (Cain, Ferejohn

and Fiorina 1987; Mayhew 1974). And although ticket splitting has declined, this personal vote persists and remains responsive to certain candidates on the ballot (Kuriwaki 2026). A surrogate cannot build this kind of reputation for the member because the voters she needs do not share the cause the surrogate stands for. In fact, a surrogate is not merely unhelpful, it is damaging. An image of her party's president reminds those voters of what they voted *against*, and for a member whose seat depends on them, that reminder carries a risk similar to that of asserting a contested position (Canes-Wrone, Brady and Cogan 2002). A member in a marginal seat therefore has reason to foreground her own presence and limit the party's. By appearing in her feed, constituents can judge her as a person, and she is able to build recognition and reputation.² For the member in a marginal constituency, then, presentation of self is not simply one option among several but the form of presentation her seat calls for.

These considerations lead to two primary expectations about the composition of members' images.

Hypothesis 1. Members from more aligned constituencies post a smaller share of images in which they themselves appear than members from more marginal constituencies.

Hypothesis 2. Members from more aligned constituencies post a larger share of images in which a co-partisan national figure appears in their place than members from more marginal constituencies.

However, we acknowledge that our account is not the only one that would predict these cross-sectional patterns. Three alternatives treat images as downstream of something else that differs between marginal and aligned members: the topics they discuss,

²We note that presence does not require agreement on policy. As Bianco (1994) argues, presence and attentiveness build the trust that allows a member latitude to depart from constituent preferences when she judges it necessary, so a member who is embedded in her community may still vote with her party in Washington.

the way they spend their time, and the resources they command. We test each of these below.

Two other possibilities also warrant attention. The first is that members post images of themselves chiefly to build name recognition. We regard this as a component of our argument rather than an alternative to it, since our claim is that marginal members present themselves in order to be known as individuals. The second is that pressure to present co-partisan national figures comes from the party rather than from the constituency. In a period of close competition for majority control, party leaders ask members to carry the party's message (Lee 2016), and aligned members may post the party's figures because leadership asks them to rather than because their constituents reward it. We acknowledge that this account predicts the same pattern as ours and that our design cannot separate the two. We regard them as complementary rather than competing: leadership may ask every member to carry the party's message, but members in aligned constituencies are the ones for whom doing so carries no electoral cost, and so they may be the ones most likely to comply or the ones most likely to be asked. A related limit is that cross-sectional variation cannot tell us whether members adapt their presentation to the seats they hold or whether seats select for members who present themselves in particular ways. Our design identifies the association between constituency alignment and presentation, and we return to the question of adaptation when we examine redistricting below.

Finally, we are careful about what our argument claims. It describes a tendency across members rather than a rule for any one of them. Aligned members who present themselves often, and marginal members who rarely do, both exist, and our claim concerns how the balance shifts across constituencies. Nor do we make any claim about belief. Presentation of self and of surrogates describe what a member puts before constituents, not what she privately takes the representative relationship to be.

Visualizing Self-Presentation in Congressional Tweets

To test our theory, we turn to the images members share on Twitter. Members communicate with constituents through several channels their offices control, including press releases (Grimmer 2013*b*), e-newsletters (Cormack 2017), and social media, which has become a central tool through which legislators reach constituents (Kaslovsky and Kistner 2025; Russell 2021; Macdonald, Hua and Russell 2026). Twitter is a widely used platform on which lawmakers routinely share political and partisan positions, publicize their activities, and communicate with constituents (Barberá et al. 2019; Golbeck, Grimes and Rogers 2010; Russell 2021). Twitter’s audience skews national, and audiences, and thus relative positioning, may vary across mediums (Green et al. 2024). However, our argument concerns what members put forward rather than who sees it, and past studies find substantial overlap in issue content (Russell and Wen 2021) and ideological self-presentation (Hassell, Heseltine and Reuning 2025) when comparing Twitter to other venues.

Beyond these channels, members also present themselves to constituents elsewhere, such as in television appearances and in-person events. The choice we study can arise in those venues as well. What distinguishes images on social media, however, is that the feed is not a sample of a member’s presentation of self but is, itself, a presentation of self—assembled by her office from the images it chooses to post. When lawmakers share images in their tweets, they choose which activities to publicize, how to depict them, and who appears: the very choices our theory concerns. A lawmaker at the county fair may post a photo of herself conversing with constituents, a photo of fair food, or no photo at all. Television coverage, by contrast, is a sample selected by others, and it over-represents members and events that attract national attention. In-person events leave no record that the member controls, which is why Fenno (1978) could observe the presentation of self only by traveling with a small number of members. We do not observe what legislators do; we observe whether they choose to depict themselves across thousands of images, in

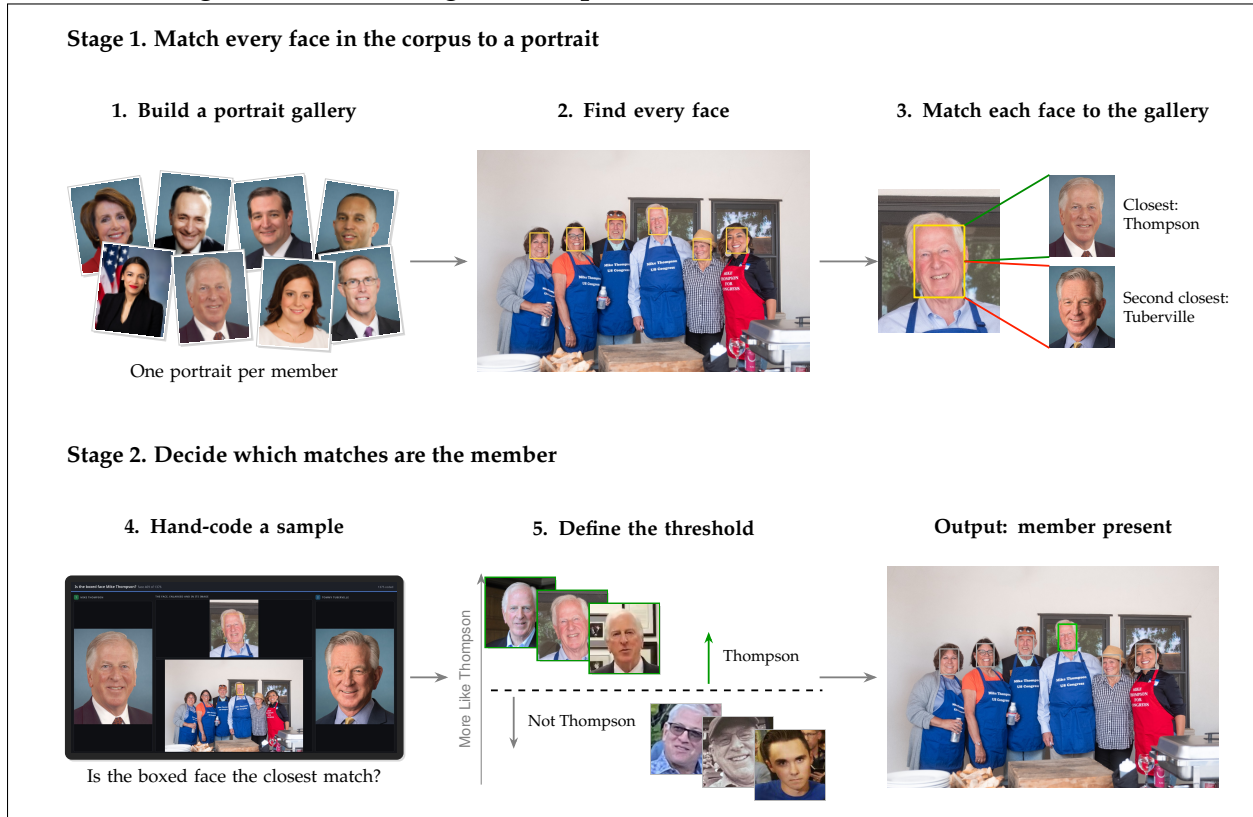
a venue that exists for every member in a consistent form. Accordingly, we treat the share of a member’s images in which she appears as the observable form of presentation of self, and the share devoted to national co-partisan figures as one observable alternative.

Data and Methods

To source images, we use data from *Tweets of Congress*, a project that collected the daily tweets sent by members of the House and Senate (as well as associated campaign, caucus, and party accounts) from June 21, 2017 to July 11, 2023 (Litell 2025). This archive contains the text of 5,068,271 tweets as well as basic metadata about each (e.g., tweet id, user screen name, time). We then create a novel corpus of images shared by members of Congress by parsing the metadata and text of each tweet. We identify all image links and programmatically download each image (where they exist as of January 2026). We identified 2,679,597 image links, of which 2,574,885 were live (approximately 4% of links were broken as accounts had been deleted or images had been removed). After excluding non-member accounts (e.g., caucus or party accounts), non-voting members, members with missing covariates, and members who posted no images in a given Congress, our dataset contains 4.3M unique tweets sent by 803 members of Congress, of which 1.7M contain at least one image.

To test our hypotheses about self-presentation, we measure whether members appear in the images they post using a facial recognition pipeline summarized in Figure 1 and detailed fully in Appendix A. To summarize: we source a portrait of each member of Congress who served during the 115th–118th Congress (January 2017 to January 2025) and compare them to every detected face in every image of our corpus using the pre-trained InsightFace `buffalo_l` model. We preserve the highest scoring portrait-face pair match and establish a threshold at which we convert these continuous similarity scores into binary match/not-match code. To choose the cutoff, one author hand-coded a stratified sample of 452 portrait-face matches, blind to the scores. Another author coded a

Figure 1: Face Recognition Pipeline to Measure Member Presence

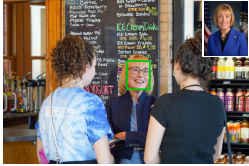
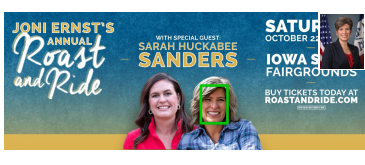
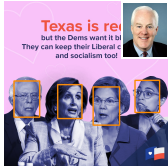
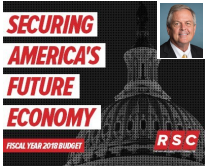


Note: Our facial recognition pipeline identifies faces in images, compares those faces to congressional portraits, and identifies likely matches. We then hand-code a sample of images to establish the threshold at which we establish a true match. Here, we follow one image posted by Rep. Mike Thompson (D-CA). Detected faces are highlighted in yellow. The green box establishes a member-match. Faces in panel 5 are drawn from Thompson’s posts and are ordered by similarity to his portrait. Those above the line are coded as matches; those below are not.

subset, which matched the first author’s coding in 85% of cases (Cohen’s $\kappa = 0.64$). We chose the threshold that maximized accuracy on a training half of the sample and assessed it on the held-out half, which achieves 90% accuracy, 92% precision, and 97% recall. We then aggregated to the image level: an image is coded as *member-present* if any face in that image is the posting member. Otherwise, an image is coded as *member-absent* (including images where no face was detected).

In Figure 2, we show examples of this measure from our corpus. In the top panel, we provide several examples of member-present images. Each identified member appears in a green box, and their portrait is inset in the top-right for reference. Here, we can see

Figure 2: Examples of Member-Present and Member-Absent Images

	1	2	3
	Member Present		
1	 Sen. Maggie Hassan (D-NH)	 Rep. Jake Auchincloss (D-MA)	 Sen. Ted Cruz (R-TX)
2	 Sen. Mark Warner (D-VA)	 Rep. Ashley Hinson (R-IA)	 Sen. Joni Ernst (R-IA)
	Member Absent		
	<i>Co-partisan president</i>	<i>Co-partisan national figure</i>	<i>Out-party president</i>
3	 Sen. Mike Braun (R-IN)	 Rep. Lance Gooden (R-TX)	 Rep. Jody Hice (R-GA)
	<i>Out-party national figure</i>	<i>Other member of Congress</i>	<i>Unidentified faces</i>
4	 Sen. John Cornyn (R-TX)	 Sen. Patrick Leahy (D-VT)	 Rep. Paul Gosar (R-AZ)
	<i>Unidentified faces</i>	<i>No face</i>	<i>No face</i>
5	 Rep. Tim Ryan (D-OH)	 Rep. Ralph Norman (R-SC)	 Sen. Jeff Merkley (D-OR)

Note: The top panel shows images in which members are present. We mark the posting member's face in a green box. The bottom panel shows images in which members are absent. We mark other people we identify with the same face-recognition pipeline in an orange box. The posting member's portrait appears inset in the top right of each image.

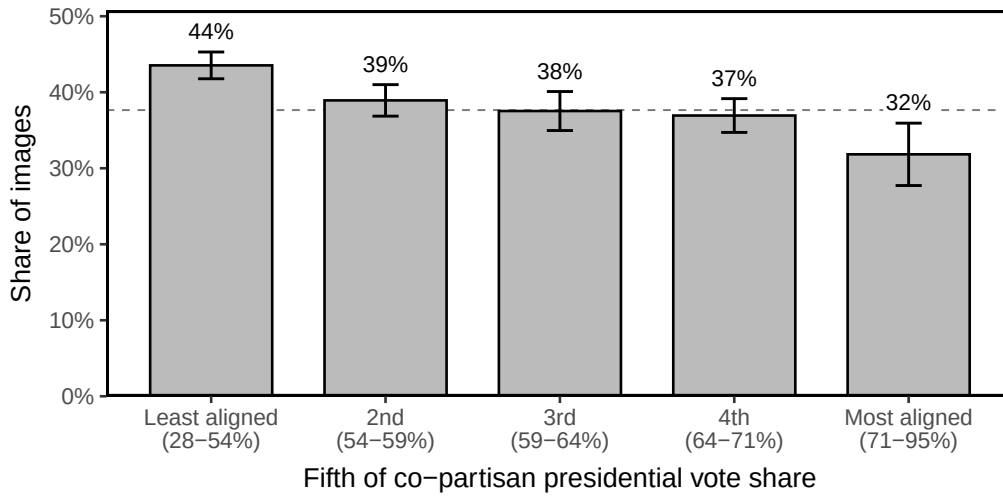
several ways in which members present themselves: interacting with constituents, delivering speeches, appearing with other elites, and advertising events. The bottom panel provides several examples of images that members post in which they do not appear. These images include a range of other people such as co-partisan elites (which we call surrogates), as well as out-partisan elites, other lawmakers, ordinary people, text-based graphics and landscapes.

Overall, 37.7% of images show the member; 62.3% do not. However, this corpus average masks substantial heterogeneity across lawmakers. Following Grimmer (2013a), we define alignment as the member’s co-partisan presidential vote share in the last election (from Amlani and Algara 2021; The Downballot 2025). In Figure 3, we sort member-Congresses into quintiles of co-partisan presidential vote share and plot, for each quintile, the image-weighted average share of images in which the member appears. Members in the least aligned fifth, those whose presidential candidate won between 28 and 54 percent of the vote in the last presidential election, appear in 44% of images they share. This proportion decreases monotonically across quintiles to 32% among the most aligned fifth—a gap of 12 percentage points. Marginal members visually present themselves more often than do aligned members, which we test more rigorously in the following section.

Empirical Approach

To test our main argument, that marginal members appear in their images more often than aligned members, we conduct a series of correlational regressions using ordinary least squares. Our unit of analysis is the member-Congress. We define our primary dependent variable as the share of images in which the member appears. Here, the denominator is all images a member posts in a given Congress and the numerator is the number of images in which they are coded as member-present. We focus on shares rather than raw counts as it better matches our theory, which concerns the overall degree to which members present themselves in their feed. Shares are comparable across members who

Figure 3: Member Presence by Constituency Alignment



Note: Bars report the share of images in which the posting member appears, by quintiles of co-partisan presidential vote share. Shares are weighted by the number of images each member-Congress posted. Error bars are 95% confidence intervals with standard errors clustered by member. The dashed line is the weighted mean across all member-Congresses (37.7%).

post more or less frequently and better simulates what a constituent might encounter scrolling through the member’s Twitter feed, while raw counts conflate the decision to post with the decision of what members show.

Our independent variable is co-partisan past presidential vote share in the district or state. We assign each member to the party they caucused with at the start of the Congress. In our models, we adjust for a suite of control variables that could bias the relationship between district alignment and image content decisions, including gender, chamber, race (including African American and Latino), party, majority party status, presidential co-partisanship, past vote share, leadership positions, and seniority. These control variables all come from the Center for Effective Lawmaking (Volden and Wiseman 2014, 2018). In our models, we include Congress fixed effects to account for common shocks within congresses, and we cluster standard-errors at the lawmaker-level. We also weight each member-Congress observation by the total number of images a lawmaker posts in a given Congress, so that high-volume posters are not proportionally diluted by low-volume

members. Given our short time series and the limited within-member variation in co-partisan presidential vote share, we do not include lawmaker fixed effects. As such, our results must be interpreted as cross-sectional comparisons.

Results: Marginal Members Appear More Often than Aligned Members

We test our primary hypothesis, that marginal members will be more likely to appear in the images they post, in Table 1. In column 1, we test our baseline specification regressing the share of images in which members appear (as a proportion of all images they share in a given Congress) on co-partisan presidential vote share. Here, the coefficient is -0.326 , which is large, negative, and statistically significant as expected. The more aligned a member is with her district, the less likely she is to appear in the images she posts. Substantively, a one standard deviation shift in co-partisan presidential vote share (about 11 percentage points) is associated with a 3.6 percentage point decline in the share of images in which the member appears, roughly 10% of the 37.7% corpus average. Put another way, the unweighted median lawmaker posts 697 images per Congress and appears in 265 of them. Holding volume fixed, another median member with 11 percentage points higher district alignment appears in 25 fewer images over the course of a Congress. This supports hypothesis 1, that members in aligned constituencies share fewer images of themselves than those in marginal constituencies.

One might be concerned about the primary alternative explanation: that images members post are downstream of what they discuss. It is well established that aligned lawmakers tend to focus their rhetoric on national figures or issues, while marginal members do not, allocating more attention toward local or constituency-specific concerns (e.g., Grimmer 2013a; Noble 2024). These rhetorical patterns may then lead members to share certain types of images. For example, an aligned member may discuss immigration and, in their Tweet, include a photo of the border wall or an ICE encounter, where they are not the focal subject. Meanwhile, a marginal member may advertise a town hall or de-

Table 1: Member Presence in Images by Constituency Alignment

	Member-Congress Level	Image Level	
	Baseline	All Topics	Policy Topics
	(1)	(2)	(3)
Co-partisan Pres. Vote Share	-0.326** (0.102)	-0.209* (0.086)	-0.221** (0.076)
Female	0.018 (0.012)	0.010 (0.010)	0.014 (0.011)
Senate	0.059*** (0.015)	0.064*** (0.013)	0.072*** (0.014)
Republican	-0.002 (0.015)	-0.010 (0.013)	-0.011 (0.012)
Majority	0.012 (0.007)	0.010 (0.006)	0.013* (0.006)
Presidential Co-Partisan	0.012 (0.008)	-0.003 (0.007)	0.003 (0.007)
Black	-0.000 (0.022)	-0.002 (0.019)	-0.013 (0.018)
Latino	-0.022 (0.017)	-0.017 (0.014)	-0.009 (0.014)
Past Vote Share	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Leadership	0.019 (0.017)	0.030* (0.014)	0.027 (0.015)
Seniority	-0.004* (0.002)	-0.003* (0.001)	-0.004* (0.001)
Congress Fixed Effects	✓	✓	✓
Topic Fixed Effects		✓	✓
Num.Obs.	2150	2189441	709338
R2 Adj.	0.161	0.093	0.053
R2 Within Adj.	0.107	0.007	0.010

Note: Results come from ordinary least squares models. In column 1, the dependent variable is the proportion of images in which the member appears, image-weighted. In columns 2 and 3, the dependent variable is an indicator for whether the image is member-present. Standard errors are clustered at the member level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

scribe her visit to a local school, sharing a photo in which she is prominently featured. In this case, the patterns we identify in column 1 would be downstream of a well-studied

rhetorical choice rather than a distinct mechanism operating through incentives for visual self-presentation.

To test this possibility, we fit a 60 topic LDA model to our full corpus of 5 million tweets (full pre-processing and fitting details are in Appendix B). These topics include a mix of policy (e.g., national debt, immigration and border enforcement, the opioid crisis), politics (e.g., Trump and Biden, the Supreme Court), and communications (e.g., town halls, local visits, birthday and holiday greetings). We assign each tweet to its most prevalent topic, and each image inherits its parent tweet's topic (as Tweets can contain more than one image). We use this label as a fixed effect in an image-level regression where we regress a binary indicator for whether the member is present in the image on the constituency's co-partisan past presidential vote share in a linear probability model.³ If, after accounting for topic, we still find that members representing aligned constituencies post a smaller share of member-present images than members representing marginal constituencies, we would conclude that the visual signal is not simply downstream of what lawmakers communicate in text.

The headline finding in columns 2 and 3 is that aligned members post fewer member-present images, *holding the Tweet topic fixed*. In column 2, the specification is over all topics and in column 3, topics that are explicitly policy-focused, like immigration, student debt, and infrastructure. Even when members discuss the same substantive policy topics in their tweets, including the same policy topics, marginal members are more likely to appear in the images they post. The coefficients are smaller in magnitude than in our baseline model without topic fixed effects, but topics explain only about a third of the gap. However, we are cautious in interpreting this finding. First, topics may be post-treatment: alignment could shape what members discuss, and conditioning on topic may absorb part of the effect. Second, topics may suffer from simultaneity: topic and image

³As all predictors are at the member-Congress level and we weight the member-Congress specification by image counts, the unweighted image level analysis produces the same coefficients. Given that the topic model assigns topics to 99 percent of images, the coefficients in these image-level models are more or less directly comparable to the member-Congress aggregated model.

may be part of the same decision. As such, we are careful not to interpret the differences between columns as the effect of alignment. Rather, these comparisons show how much of the gap remains among tweets on the same broad topics: about two-thirds.

We address two other alternative explanations and report results in Table C1. First, member-presence in images may reflect differences in how different types of lawmakers spend their time. Existing literature argues that aligned members spend more time on nationally-oriented Washington work while marginal members prioritize their constituency (Ashworth and Mesquita 2006; Kaslovsky, Moskowitz and Schneer N.d.). We might then predict that marginal members have ample opportunities to share photos of themselves speaking to or engaging with constituency groups while aligned lawmakers, busy with the policy process, share text-based graphics, images of Washington, or salient political figures. The images they share, then, reflect how these different types of legislators spend their time. To test this alternative, we compare the relationship between constituency alignment and self-presentation on days when members cast at least one recorded roll-call vote, which establishes that a member was in the Capitol for at least part of the day. If visual self-presentation is mechanically downstream of how legislators spend their time, we would expect the gap between aligned and marginal members to substantially narrow or disappear on days when they are in Washington. In Table C1, column 1, we continue to find that marginal members share more images of themselves than aligned members even on days when they are in the Capitol. The effect is slightly attenuated relative to the baseline model, but the estimate remains negative and statistically significant.

Second, member-presence may reflect differences in member resources. Images of oneself may be costlier to produce as they require the member's participation; text-based graphics can be cheaply produced by a staffer while the member does other work. If marginal members have access to more resources (e.g., campaign receipts), they may post more images of themselves as a byproduct. In Table C1, column 2, we control for the

logged total receipts plus one raised by each member in the cycle preceding the Congress in which they post a given image (from DIME). We observe a positive and significant relationship between campaign receipts and posting images of oneself (consistent with our theorized alternative), however, the coefficient on alignment is almost identical to that of the baseline model. Granted, this variable may be post-treatment if member alignment drives funding. As a second test of the resources hypothesis, in column 3, we subset our analytic population to House official Twitter accounts. All House members receive Members' Representational Allowance, funding for official activities granted by a formula that standardizes resources across offices. At the same time, House ethics rules prohibit the use of campaign funding for official communication. By focusing on House official accounts, we can eliminate the use of campaign funding to produce official communications while comparing offices funded through an MRA formula designed to equalize operating capacity. Here, we continue to see the theorized patterns: aligned members post fewer member-present images.

In Table C3, we also run a series of other robustness tests. We show that our main results hold when we exclude 2020 to account for the most intense period of the COVID-19 Pandemic, when we exclude images in our corpus that come from video stills, and when we exclude images from quote tweets and retweets. The latter is of particular importance given that one explanation for our findings could be that aligned lawmakers simply repost more party content than marginal members. However, this result indicates that even excluding such content, the pattern persists, although the coefficient is attenuated. Ultimately, we consistently find that aligned members post a smaller share of images of themselves than marginal members.

Our design is cross-sectional, and as such, it cannot tell us whether members strategically adapt their self-presentation to suit their changing constituencies or whether members are selected for exhibiting a specific presentational style. We test these competing expectations by looking at member-presence in images after 2020 House redistricting.

Among the sample of lawmakers who served in the 117th (2021–2023) and 118th (2023–2025) Congresses, those whose districts became more aligned after new maps were implemented in 2022 decreased their share of member-present images (-0.036) but the estimate is imprecise and not statistically significant. Although this coefficient is consistent with adaptation, we treat the result as inconclusive, especially given the short time window and limited variation in alignment across the redistricted maps.

Do Surrogates Fill the Gap?

If marginal members' feeds are more heavily populated with images of themselves, what are aligned members posting instead? First, we test our hypothesis that some of that gap is filled by images of co-partisan national figures: salient figures of the member's party posted without the member, the pattern we interpret as national surrogacy. We then turn to unpacking what explains the rest of the gap.

To test this hypothesis, we first define the set of national figures, which includes the parties key leaders (Trump across the sample, Biden beginning with his primary run in the 116th and through his presidency, and Clinton in the 115th given her 2016 candidacy), the two serving vice presidents, the major 2020 and 2024 primary candidates, the four primary congressional leadership positions, and a set of the most salient members of Congress (who are not already included in any other aforementioned group). To define this latter set of actors, we collect the daily Wikipedia page view count of every lawmaker who served in our sample.⁴ We aggregate these statistics to the month level, and for every Congress that lawmaker served, we compute the median monthly page view count. For each party, we denote the top ten members by page view count as national figures (excluding those like Bernie Sanders and Ron DeSantis who are already captured by our primary candidate measure). Members like Alexandria Ocasio-Cortez, Marjorie Taylor

⁴In each Congress, we compute page views over the entire Congress; salience is measured over the entire period.

Greene, and Joe Manchin appear on this list.⁵ We define the full set of actors in Table A3 of the Appendix.

To identify these figures in images, we use the same facial recognition pipeline outlined above to identify, for each face, whether it matches another sitting lawmaker or one of the national figures who is not a sitting member of Congress. As described in Appendix A, we do this in two stages, first identifying presidents Biden and Trump and then identifying all others. Among held-out detected faces whose best matching portrait belong to the relevant group, we can identify presidents with 94% accuracy and everyone else with 93% accuracy. Although precision is high across both groups, recall is low (61%) among the non-presidents set. That is, we can be confident that, when we identify someone, they actually appear. However, we are likely understating the degree to which others appear in posting members' images. After identifying this set of individuals, we aggregate to the image level, labeling an image as a co-partisan national figure when a member of Congress posts an image of a co-partisan national figure and they do not appear in the image themselves.⁶ We provide two examples of such images in 3-1 and 3-2 of Figure 2. There, Senator Mike Braun (R-IN) shares a photo of President Trump and Rep. Lance Gooden (R-TX) posts a photo of Republican Minority Leader Kevin McCarthy.

Table 2 supports our hypothesis that aligned members devote a larger share of their feeds to their party's national figures. In column 1, we find that constituency alignment is positively associated with the share of a member's images that show a co-partisan national figure without her. In columns 2 and 3, we decompose this share into co-partisan party leaders (Trump, Biden, Clinton), the most nationalized and well-known figures, and all others. Here, we see that the coefficient is equally composed of the key party leader and other national figures. Surrogate images constitute about two percent of the corpus

⁵Although a figure like Joe Manchin, a partisan maverick, is likely not being presented by strong Democrats as a surrogate, we nonetheless include him in our operationalization to avoid any bias from excluding members after seeing the list. The inclusion of these types of figures bias against a finding of surrogate presentation.

⁶Images salient members post of themselves (e.g., Sanders posting himself) count as member-present and do not count as co-partisan national figures.

Table 2: Surrogate Presence in Images by Constituency Alignment

	Surrogate Share	Key Party Leader Only	Excl. Key Leader
	(1)	(2)	(3)
Co-partisan Pres. Vote Share	0.050*** (0.014)	0.024** (0.009)	0.026*** (0.007)
Female	-0.001 (0.001)	-0.002* (0.001)	0.000 (0.001)
Senate	-0.005*** (0.002)	-0.002* (0.001)	-0.003*** (0.001)
Republican	0.006** (0.002)	0.002* (0.001)	0.004*** (0.001)
Majority	0.001 (0.001)	-0.002* (0.001)	0.003*** (0.001)
Presidential Co-Partisan	0.011*** (0.002)	0.012*** (0.001)	-0.001 (0.001)
Black	0.006 (0.004)	-0.001 (0.001)	0.007* (0.003)
Latino	-0.000 (0.004)	-0.002 (0.002)	0.002 (0.003)
Past Vote Share	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Leadership	0.001 (0.002)	0.001 (0.001)	0.001 (0.001)
Seniority	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Congress Fixed Effects	✓	✓	✓
Num.Obs.	2150	2150	2150
R2 Adj.	0.247	0.320	0.211
R2 Within Adj.	0.206	0.313	0.137

Note: Results come from weighted ordinary least squares models estimated on member-congress proportions. The dependent variable is the share of images in which a surrogate appears. Observations are weighted by the number of images. Standard errors are clustered at the member level. * $p < 0.05$;

** $p < 0.01$; *** $p < 0.001$.

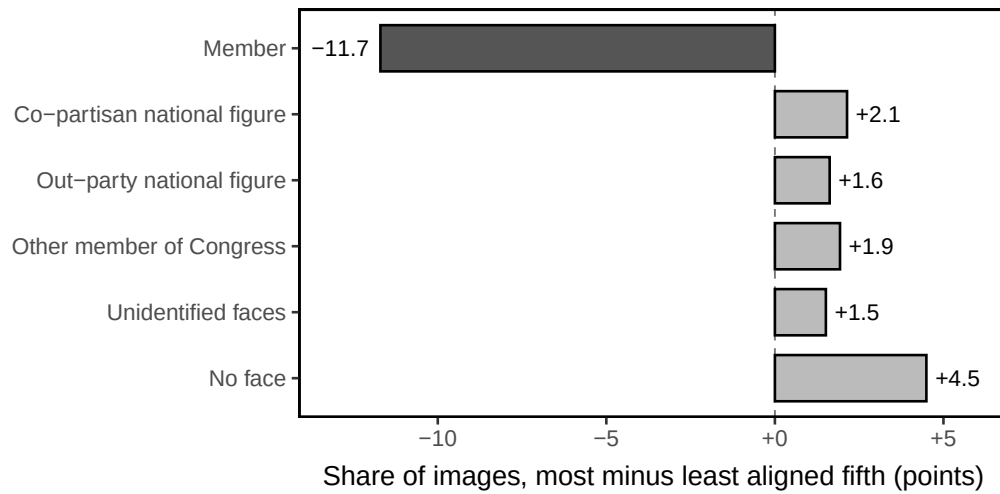
overall; this statistic, however, understates their contribution to the member-presence *gap* between marginal and aligned members. It also understates the surrogate share itself: recall for non-president national figures is 61% (Table A2), so the non-president half of the coefficient in Table 2 is a lower bound.

Next, we examine how much of the member-presence gap surrogate images account for. Here, we compare the least and most aligned fifth of our sample, partitioning images into six mutually exclusive categories: member-presence, co-partisan national figures, out-party national figures, other members of Congress, unidentified faces, and images with no detected face.⁷ We report these differences in Figure 4 and examples of each type can be found in Figure 2. As demonstrated earlier, marginal members appear in about 12 percentage points (11.7) more images than aligned lawmakers. So what explains this gap? About one-fifth (2.1 percentage points, 18%) is explained by co-partisan national figures, whose share roughly triples from 1% among the least aligned fifth to 3.1% among the most aligned. Here, we identify a clear gradient between alignment and surrogate presentation. However, we recognize that while we document a real pattern, it comprises a modest share of the overall gap in member-presence between aligned and marginal lawmakers. The remaining categories can help us describe the other four-fifths of the gap.

Beyond surrogates, another 1.6 percentage points (14%) of the gap is made up of out-party foils: Republicans posting images of Biden, Pelosi, and Alexandria Ocasio-Cortez, and Democrats posting images of Trump and McConnell. Surrogates and out-party foils are circulated more or less equally among the most aligned members. Sharing these opposition figures is consistent with another type of nationalization more focused on partisan messaging (Lee 2016; Noble 2024). Another 1.9 percentage points (17%) is allocated to images of other members of Congress beyond the most salient figures. These images are ambiguous: a colleague may stand in for the party's cause or simply for the ordinary work of a legislation, and we do not fold them into either the nationalized or the local side of the balance. Next, 1.5 percentage points (13%) are unidentified faces. These may be other elites who fall outside of those defined as surrogates or out-party foils (e.g.,

⁷Although images can span categories (e.g., an image with a co-partisan national figure and another member of Congress), we categorize images sequentially in this order, which prioritizes those of theoretical interest.

Figure 4: Decomposing the Member-Presence Gap



Note: Bars indicate the difference in the share of each image type between the most aligned and marginal members, in percentage points. We assign each image in order from top to bottom, so types are mutually exclusive. Shares are weighted by the number of images each member-Congress posted.

Supreme Court justices, state or local politicians) or ordinary people like constituents or figures who stand in for key interest groups (e.g., blue collar workers, teachers). Finally, the largest portion of the gap, 4.5 percentage points (38%), is images in which no face was detected. These are typically messages with no messenger: partisan talking points, constituency announcements, and holiday well wishes. Although these images are the largest contributor in absolute terms, they rise by just 15 percent from their much larger base (29 to 34 percent). Surrogates are thus the category most responsive to alignment, though not the one that fills most of the gap.

Finally, what explains the gap in member presence? A smaller share can arise in two ways: aligned members may post fewer images of themselves (i.e., withdrawal), or they may post about as many but surround them with more images of other kinds (i.e., dilution). When we model our dependent variables as counts rather than shares (Table C4), we show that dilution, rather than withdrawal, explains the gap. We find that aligned members post about as many images of themselves as marginal members, but post more

images of other types, including co-partisan and out-partisan figures, other lawmakers, and content with no detected face. Thus, the aligned member remains in her feed, but the party's figures and the party's message take up more of the space around her. Marginal members, by contrast, curate a smaller feed in which they, not their party's messengers, are more central.

Member Presence is Associated with Greater Recognition among Constituents

To this point, we have focused on the supply side of self-presentation. However, one might wonder whether these differences in style are related to members' reputations at home. Our argument is that marginal members show themselves more often to cultivate a personal vote; aligned lawmakers do not, focusing on party surrogates who signal particular political commitments. Under our theoretical logic, we would expect these strategies to benefit the lawmakers using them in equilibrium, but through different mechanisms. In particular, lawmakers who post images of themselves should be better known among their constituents.

To provide evidence of this relationship we turn to data from the Cooperative Elections Study (CES) from 2017–2023. In these years, the survey provides respondents with the name of their House member and both senators and then asks them if they have ever heard of the person and, if so, the party affiliation of that person. Individuals can respond with “never heard of person,” as well as the party labels, or “not sure.” Here, we focus on the “never heard of person” responses. Importantly, we recognize that even if someone has never heard of their representative, they may still vote for that person (which would be consistent with our theory where aligned lawmakers win by sharing images that promote their partisan commitments). However, the key logic is that posting more images of oneself should be associated with greater recognition, which should help candidates

cultivate a personal vote (Kam and Zechmeister 2013; Mann and Wolfinger 1980).

For each lawmaker in our corpus, we compute the share of respondents saying “never heard of person” using the annual CES weights, aggregate to the two-year Congress level, and regress it on the share of member-present images they posted in that Congress. We also include a number of important controls. We account for past co-partisan presidential vote share as marginal members may be more well-known due to running in more competitive races, and we also control for campaign receipts, as members may use resources to increase recognition. We also include controls for the share of policy and political topics members discuss. These controls isolate variation in recognition driven by the content of member messaging. Finally, we control for member extremity, as ideological extremists may receive more attention and thus be better known. We also control for whether a member is one of the most salient figures we identified earlier: either a national figure, leader, or salient lawmaker. We include the other controls in our baseline models and cluster standard errors by member and state (to account for multiple ratings of the same member by the same respondents who are clustered within a given state). In some models, we weight by the number of respondents and include member fixed effects.

The results in Table 3 provide some evidence that lawmakers who appear more in their images are better known by constituents. In column 1, which excludes weights and pools across the House and Senate, we observe a small but statistically significant decrease in the number of respondents saying they have “never heard of” their representative. When we weight by the number of respondents in column 2, we observe a slightly larger decrease. Practically, a one standard deviation increase in the member-present share is associated with a 0.6 percentage point decrease in the share of respondents who say they haven’t heard of the member. Although this may seem small, it represents about an eight percent decline over the mean. These results are cross-sectional, so in columns 3–5, we add member fixed effects to isolate within-member change. Although the coefficient is not statistically distinguishable from zero in the pooled sample and House model, we

Table 3: Relationship Between Member Presence and Share of Constituents who have Never Heard of Member

	Both Chambers			House Only	Senate Only
	(1)	(2)	(3)	(4)	(5)
Member Presence Share	-0.018* (0.008)	-0.039* (0.019)	-0.011 (0.011)	0.000 (0.013)	-0.029* (0.013)
Co-partisan Pres. Vote Share	0.069*** (0.019)	0.099** (0.030)	-0.069 (0.062)	-0.032 (0.072)	-0.124 (0.117)
Politics Tweet Share	-0.042** (0.014)	-0.020 (0.019)	-0.006 (0.018)	-0.026 (0.030)	0.023 (0.023)
Policy Tweet Share	-0.023 (0.018)	-0.017 (0.019)	0.002 (0.015)	-0.009 (0.024)	0.009 (0.027)
Salient Member	-0.017** (0.005)	-0.019** (0.006)	-0.006 (0.003)	0.000 (0.009)	-0.005 (0.003)
Ideological Extremity	0.038* (0.014)	-0.003 (0.011)			
Logged Campaign Receipts	-0.006*** (0.001)	-0.003*** (0.001)	-0.001** (0.001)	0.000 (0.003)	-0.002*** (0.000)
Female	-0.010*** (0.002)	-0.003 (0.002)			
Senate	-0.007* (0.004)	0.001 (0.003)			
Republican	0.002 (0.003)	0.006 (0.005)			
Majority	0.001 (0.002)	-0.000 (0.002)	0.002 (0.002)	0.001 (0.002)	0.005* (0.002)
Presidential Co-Partisan	-0.004 (0.003)	-0.000 (0.003)	-0.000 (0.002)	-0.002 (0.003)	
Black	0.001 (0.005)	-0.001 (0.005)			
Latino	0.018*** (0.003)	-0.006 (0.008)			
Past Vote Share	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)
Leadership	-0.005 (0.005)	-0.007 (0.004)	-0.004 (0.006)	-0.011 (0.009)	0.001 (0.007)
Seniority	-0.001*** (0.000)	-0.001* (0.000)			
Respondent Weights		✓	✓	✓	✓
Congress Fixed Effects	✓	✓	✓	✓	✓
Lawmaker Fixed Effects			✓	✓	✓
Num.Obs.	2092	2092	1876	1503	366
R2 Adj.	0.156	0.229	0.560	0.364	0.763
R2 Within Adj.	0.137	0.215	0.004	-0.005	0.032

Note: Results come from ordinary least squares models estimated on member-congress proportions. The dependent variable is the share of respondents in a given congress who say they have “never heard” of their member of Congress when presented with the name. Observations in columns 2-5 are weighted by the number of respondents per member-Congress. Standard errors are clustered by member and state.

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

observe a negative and statistically significant effect in the Senate model. These estimates may differ because the survey has fewer respondents per House district, and estimates are noisier, or these differences may represent sincere differences between chambers.

Although these results are consistent with our theory, we cannot draw a causal conclusion that appearing in more images causes recognition to increase. We cannot conclude that constituents observe these images, and we cannot rule out that member-presence is a byproduct of other behaviors that boost recognition (e.g., holding town halls). However, these models do provide modest evidence of a link between self-presentation and recognition, a key precursor to cultivating a personal vote. If marginal members share images of themselves to develop a personal vote, and such self-presentation matters, this is exactly what we would expect to see.

Conclusion

American politics have nationalized: politicians and voters increasingly focus on national politics at the expense of candidate-specific or local issues (Hopkins 2018). These trends have shaped how members speak (Ban and Kaslovsky 2025; Grimmer 2013a; Noble 2024); here, we argue it can also affect *who* members place before constituents as the representative. We theorize that members in aligned constituencies, whose electoral environment incentivizes a focus on shared national and partisan commitments, dilute their presence by presenting co-partisan national figures. In comparison, marginal lawmakers, who must win over ambivalent or out-party voters, are more likely to place themselves before constituents and eschew the presentation of party figures. To test these hypotheses, we construct a new dataset of congressional images and use facial recognition technology to identify member and co-partisan national figure presence in 2.2 million Twitter images. We support our general theory, however, we also find that co-partisan national figures, who we interpret as surrogates, comprise only about one-fifth of the difference

in member-presence. We explore the remaining 80% which is made up of out-party foils, other lawmakers, unidentified individuals, and messages without faces. Finally, we provide some evidence of the behavioral implications: lawmakers who present themselves more in images are better known by constituents.

These findings contribute to our understanding the non-verbal side of presentation of self (Anastasopoulos et al. 2024; Peng 2021; Xi et al. 2020). This literature has so far focused on choices members make conditional on appearing in their images. However, we address a series of prior consideration: do members present themselves at all and if not, who do they present in their stead? This latter question also connects the literature on self-presentation to surrogate representation (Mansbridge 2003). Where this literature has established the concept and explored who may be seen as a surrogate (English, Pearson and Strolovitch 2019), none have considered the supply side. Here, we ask whether members *supply* surrogates and examine the incentives to do so. Our logic follows that of the personal vote (Cain, Ferejohn and Fiorina 1987; Mayhew 1974), and we identify how members may cultivate one through their visual self-presentation.

Of course, our study is just one early effort to examine how members visually promote themselves. We focus on one important dimension—member presence—but there is certainly more to explore. For example, conditional on member presence, do these members vary the ways in which they do appear cross-sectionally (e.g., do rural members provide images of themselves as farmers) or across different venues (e.g., do they dress differently in rural versus urban settings)? Or relatedly, who do members most often appear with? Further, beyond member presence, we find that the largest category of images in our corpus are those without faces. These include partisan messaging, constituency announcements, and landscapes. These presumably vary in the amount of nationalized content and constituency outreach as well. Finally, we examine only images, but members increasingly present videos of their Washington and district work. These provide a potentially rich vein to study member self-presentation.

Fenno (1978) argued that the most important part of presentation of self was not what members said, but rather, the non-verbal expressions they gave off when placing themselves before constituents. Through these encounters, constituents came to know and trust their members, providing some leeway in their Washington work. Congressional politics have changed since the Textbook Congress of the 1960s and 1970s, but we often still think in terms of the member as the representative. But voters may think differently. They pay little attention to politics, and few can name or identify their representatives in the House (Delli Carpini and Keeter 1997). When members step out of the frame, whether to provide a surrogate or post a partisan message, they likely make it easier for voters to think in terms of parties and harder for them to recognize their representatives as people they can know and trust.

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Online Supporting Information: Picturing Representation

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A Member and National Figure Presence Coding

To measure whether members of Congress and nationalized surrogates appear in images, we start by sourcing a portrait of each member who served during the 115th–118th Congress (January 2017 to January 2025), the Congresses for which we have tweets. These portraits were sourced from `unitedstates.github.io`. If that source did not have a portrait, or that portrait was poorly formatted, we sourced a portrait from Wikipedia or another suitable source. We also source portraits of Presidents Trump and Biden, Vice Presidents Pence and Harris, all cabinet members and Supreme Court Justices who served during this period, and all major 2020 and 2024 presidential primary candidates who remained through the first primary contest. In some cases, individuals overlapped (e.g., Bernie Sanders, Ron DeSantis), but we collect only one portrait for each, and in these cases, defaulted to their `unitedstates.github` image.

We then use the pretrained InsightFace `buffalo_l` model to detect faces in each image, representing each as a unique multidimensional embedding vector. We conduct this process in steps. First, we assess whether any faces are detected in the image. If so, we embed each face. If not, we upscale the image and try again. If faces are detected, we then embed them. If faces are still not detected, we continue to the next image. The end result is a matrix where each row is a detected face, nested within an image. We repeat this process for the portrait gallery, embedding each reference portrait. Then, for each face in the corpus, we compare its embedding to every embedding in our portrait gallery, preserving the top two matches by cosine similarity.

These similarity scores do not, in and of themselves, tell us whether a face is actually the matching person. To establish a match, we must choose a threshold at which we convert continuous scores to a binary match label. We select those thresholds separately for three different groups: the posting member, the serving presidents, and all others.⁸ To select and validate the threshold for posting members (i.e., the member sharing the image appears in it), we condition on faces where the best matching portrait is that of the member who posted it. We then take a stratified random sample: up to 25 faces per similarity score bands of 0.05 across the 0–1 range. As some bands contain fewer than 25, the final sample can contain fewer than 500 images. We repeat this sampling process for presidents (conditioning on images where the president is the best match) and for all others (conditioning on faces where the best match is neither the poster nor a president). In Table A1, we report the number of images in each group.

We then shuffled these groups together. Then, for each face, one of the authors reviewed the best-matching portrait, the runner-up portrait, the image itself with the face boxed, and an enlarged crop of the face. Blind to the similarity scores, the author coded whether the face is: the best-matching person, the runner-up, neither person, or uncertain. A face was coded as the best-matching person when the author was reasonably confident in making that decision. Those cases included the obvious, such as a well-lit, front-facing depiction or super-imposed head-shot added to graphics. They also included

⁸We split these samples ex-ante because the same similarity score is more likely to be a true match for some groups (e.g., presidents, who are frequently photographed and easily recognizable) than others. Ex-post, and as shown below, the resulting thresholds ended up being relatively close to one another.

Table A1: Hand Codes on the Face Validation Sample

Group	Total Faces	Best	Runner-Up	Neither	Uncertain
Poster	452	348	3	38	63
President	449	366	1	72	10
Other	475	323	4	98	50

Note: Each cell reports the number of sampled faces assigned each code.

more difficult cases where the author was still reasonably confident despite poor lighting, a side profile, a face in sunglasses or a hat, a back view. A face was coded as the runner-up under those same circumstances for the second-best matching portrait. A face was coded as neither when the author was confident that neither the best-matching person nor the runner-up matched. Finally, a face was coded as uncertain when the author was not confident in any of the aforementioned codes. This label was given most often when faces were poorly lit or when individuals were wearing sunglasses, hats, or masks. In this hand-coded sample, the best-matching faces were coded as the member and all other labels were coded as not the member. In Table A1, we report the counts of each code per group.

To assess the reliability of these hand codes, the other author independently coded a stratified subset of these images, approximately 100 per group (282 total). In assessing presence versus non-presence, the two authors agreed in 92% of cases overall, with a Cohen’s Kappa of 0.81, which conventionally represents strong agreement. Within each group, the authors agreed in 85% ($\kappa = 0.64$), 98% ($\kappa = 0.94$), and 94% ($\kappa = 0.86$) of cases respectively. Taken together, the results indicate strong agreement between the two authors.

We then matched the original author’s hand codes to their cosine similarity scores and randomly split faces approximately in half within each group band (ensuring faces from the same images did not appear on both sides) to create three stratified training and test sets. For each group, we assess classification accuracy (i.e., whether the person was depicted or not) at each similarity score in the training set, selecting the maximum (weighted by each band’s share of faces in the corpus). We report in-sample accuracy on the training set as well as out-of-sample accuracy, precision, and recall on the test set in Table A2. For posting members and presidents, out-of-sample accuracy, precision, and recall are high, all exceeding 90%. While accuracy is also high for the third group, precision is somewhat lower (88%), and recall is substantially lower (61%). These metrics condition on detected faces whose closest matching portrait belongs to the relevant group. They indicate that we can be fairly confident that, when we identify someone, they actually appear. However, we are likely understating the degree to which others appear in posting members’ images.

Once a face clears the associated threshold, we assign that face a role given the Congress in which the image was posted. These roles include:

- **The posting member:** the member who posted the image.

Table A2: Presence Rule Performance by Group

Group	Threshold	In-Sample	Out-of-Sample		
		Accuracy	Accuracy	Precision	Recall
Poster	0.30	89.8	90.2	92.3	97.1
President	0.22	96.5	93.8	92.5	100.0
Other	0.30	97.4	93.1	87.9	61.2

Note: The threshold is the minimum cosine similarity score required to assign a match. Accuracy, precision, and recall are percentages, weighted by each band's share of the group's faces in the corpus. These metrics condition on detected faces whose closest matching portrait belongs to the relevant group.

- **Primary party leader:** President Trump throughout the entire sample, Hillary Clinton in the 115th Congress given her 2016 candidacy, and President Biden beginning in the 116th Congress (2019-2020) when he ran for president and through his full term.
- **National figures:** the sitting Vice President during their tenure (Pence and Harris); the major 2020 and 2024 presidential primary candidates in the 116th and 118th Congresses; the serving congressional leaders (Speaker, House Minority Leader, Senate Majority and Minority Leaders); and the ten most salient lawmakers of each party in a given Congress, excluding all aforementioned individuals and cabinet members. Salient members are those who have the highest median monthly English-language Wikipedia page views during that Congress, counting visits to the member's article and its associated redirects.
- **Other lawmakers:** any other member of the House or Senate serving that Congress who does not meet one of the definitions above.
- **Unidentified:** any face whose closest matching face is below the threshold.

As roles are assigned at the Congress level, members who enter Congress late or leave early are identified for that whole Congress. Thus, we capture salience and prominence within the Congress rather than strictly at the time the image was posted. In Table A3, we list all national figures for the congress in which they are relevant.

Table A3: National figures in each Congress, by party and role

Party	Role	Names
115th Congress		
R	Party leader	Donald Trump
	Vice president	Mike Pence

Table A3: National figures in each Congress, by party and role (*continued*)

Party	Role	Names
D	Congressional leaders	Mitch McConnell; Paul D. Ryan
	Salient lawmakers	Devin Nunes; Jeff Flake; John McCain; Lindsey Graham; Marco Rubio; Orrin G. Hatch; Rand Paul; Susan M. Collins; Ted Cruz; Trey Gowdy
	Party leader	Hillary Clinton
	Congressional leaders	Charles E. Schumer; Nancy Pelosi
	Salient lawmakers	Al Franken; Bernard Sanders; Beto O'Rourke; Cory A. Booker; Dianne Feinstein; Elizabeth Warren; Joseph P. Kennedy III; Kamala D. Harris; Kirsten E. Gillibrand; Maxine Waters
116th Congress		
R	Party leader	Donald Trump
	Vice president	Mike Pence
	Primary candidates	Bill Weld; Joe Walsh; Rocky De La Fuente
	Congressional leaders	Kevin McCarthy; Mitch McConnell
	Salient lawmakers	Dan Crenshaw; Jim Jordan; Kelly Loeffler; Lindsey Graham; Liz Cheney; Martha McSally; Matt Gaetz; Mitt Romney; Rand Paul; Ted Cruz
D	Party leader	Joe Biden
	Primary candidates	Amy Klobuchar; Andrew Yang; Bernard Sanders; Deval Patrick; Elizabeth Warren; Michael Bloomberg; Michael F. Bennet; Pete Buttigieg; Tom Steyer; Tulsi Gabbard
	Congressional leaders	Charles E. Schumer; Nancy Pelosi
	Salient lawmakers	Adam B. Schiff; Alexandria Ocasio-Cortez; Cory A. Booker; Dianne Feinstein; Elijah E. Cummings; Ilhan Omar; John Lewis; Joseph P. Kennedy III; Kamala D. Harris; Rashida Tlaib
117th Congress		
R	Party leader	Donald Trump
	Congressional leaders	Kevin McCarthy; Mitch McConnell

Table A3: National figures in each Congress, by party and role (*continued*)

Party	Role	Names
D	Salient lawmakers	Adam Kinzinger; Dan Crenshaw; Lauren Boebert; Liz Cheney; Madison Cawthorn; Marjorie Taylor Greene; Matt Gaetz; Mitt Romney; Rand Paul; Ted Cruz
	Party leader	Joe Biden
	Vice president	Kamala D. Harris
	Congressional leaders	Charles E. Schumer; Nancy Pelosi
R	Salient lawmakers	Alexandria Ocasio-Cortez; Bernard Sanders; Cory A. Booker; Dianne Feinstein; Elizabeth Warren; Ilhan Omar; Joe Manchin, III; Kyrsten Sinema; Mark Kelly; Patrick J. Leahy
	Party leader	Donald Trump
	Primary candidates	Asa Hutchinson; Nikki Haley; Ron DeSantis; Vivek Ramaswamy
	Congressional leaders	Kevin McCarthy; Mike Johnson; Mitch McConnell
D	Salient lawmakers	George Santos; J.D. Vance; Lauren Boebert; Lindsey Graham; Marjorie Taylor Greene; Matt Gaetz; Mitt Romney; Nancy Mace; Ted Cruz; Tim Scott
	Party leader	Joe Biden
	Vice president	Kamala D. Harris
	Primary candidates	Dean Phillips; Jason Palmer; Marianne Williamson
R	Congressional leaders	Charles E. Schumer; Hakeem S. Jeffries
	Salient lawmakers	Adam B. Schiff; Alexandria Ocasio-Cortez; Bernard Sanders; Cory A. Booker; Dianne Feinstein; Elizabeth Warren; Ilhan Omar; John Fetterman; Nancy Pelosi; Robert Menendez

B Topic Model

Here, we describe the pre-processing, vocabulary, model selection, and topic assignment and labeling for the LDA topic model used in Table 1.

Preprocessing. We pre-process the text of each tweet by unescaping HTML entities, stripping URLs and user handles, removing hashtag symbols (but retaining hashtag words),

and lower-casing all characters. We then tokenize the text into unigrams, dropping tokens shorter than three characters as well as English stopwords using the NLTK stopword list.

Vocabulary. To build our vocabulary, we retain words that appear in at least 0.01% of tweets and no more than 95% of tweets. Any tweet with at least five in-vocabulary tokens is used to train the model. Tweets with one to four in-vocabulary tokens receive a topic assignment via the fitted model later (described below).

Model selection. To select the number of topics K , we conduct a grid search over $K \in \{20, 30, 40, 50, 60, 70, 80, 100, 120, 150\}$. For each candidate value, we fit three LDA models with different random seeds on the same 15% random sample of the training corpus. We compute the coherence score. Coherence plateaus between $K = 30$ and $K = 70$, with $k = 40$ scoring highest and $k = 60$ second. After reviewing the top word clusters of these two models, we select $K = 60$ as it does a better job splitting distinct keywords into separate topics. However, we do not claim that $k = 60$ is optimal or that our labels reflect validated human judgement. Rather, we argue that any reasonable topic model will group similar tweets, and when used as fixed effects, absorb variation in what lawmakers discuss. Our argument does not rely on this model being the best description of the underlying corpus we analyze. We replicate our results when we set $K = 40$ in Table C2.

Final model and topic assignment. We fit the final LDA model with $K = 60$ on the full training corpus. Then we assign each tweet to its maximal topic. For tweets that were excluded from training (those with fewer than five in-vocabulary tokens but at least one), we compute topic assignments using the fitted model and assign a primary topic in the same way.

In Table B1, we report the five most probable words in a topic, that topic’s share of the corpus, and broad category code that we assigned to each topic after observing the full set of topics. These categories include: policy, politics, communication, ceremonial messages, and incoherent topics. We then label each topic with a conventional label sourced from the keywords.

Table B1: Topic Words, Corpus Shares, and Category Codes

Topic	Share	Top Words	Category	Sub-label
0	0.55%	student, housing, debt, loan, financial	Policy	student debt and housing
1	0.65%	food, enough, politics, supply, table	Incoherent	–
2	1.77%	vote, rep, republican, voted, republicans	Politics	floor votes, parties
3	1.95%	first, congratulations, congressman, year, john	Ceremonial	congratulations, ceremony
4	1.22%	crisis, address, fentanyl, challenges, combat	Policy	opioid crisis

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Table B1: Topic Words, Corpus Shares, and Category Codes (continued)

Topic	Share	Top Words	Category	Sub-label
5	1.25%	office, call, help, please, hours	Comms	office hours, constituent services
6	1.56%	court, supreme, justice, decision, crime	Politics	courts
7	1.07%	security, national, spending, debt, social	Policy	social security, spending
8	1.44%	thank, los, work, para, que	Incoherent	Spanish-language, thanks
9	0.94%	twitter, trust, data, media, vaccines	Politics	social media and covid
10	3.01%	great, last, county, night, week	Comms	local visits
11	2.63%	join, tomorrow, visit, town, learn	Comms	town halls and events
12	1.79%	make, every, next, sure, day	Incoherent	generic phrases
13	1.53%	safe, keep, stay, home, weather	Policy	severe weather
14	2.91%	never, lost, loved, ones, anti	Ceremonial	tragedy
15	1.77%	infrastructure, inflation, build, step, work	Policy	infrastructure
16	0.13%	free, essential, speech, feel, rail	Incoherent	–
17	0.99%	house, white, republicans, floor, rules	Politics	legislative procedure
18	0.19%	new, york, times, jersey, nyc	Incoherent	place-based phrases
19	1.21%	state, capitol, welcome, ccp, georgia	Incoherent	–
20	2.61%	china, war, accountable, hold, world	Policy	foreign policy
21	0.77%	children, kids, parents, fund, military	Policy	family funding
22	2.81%	biden, administration, admin, trump, general	Politics	executive branch
23	1.39%	states, united, since, record, year	Ceremonial	records
24	3.50%	act, bill, legislation, passed, senate	Politics	legislative action
25	1.29%	abortion, colleagues, letter, led, joined	Policy	abortion and reproductive services
26	3.67%	service, honor, veterans, women, today	Ceremonial	veterans and military service
27	3.30%	biden, president, trump, joe, ukraine	Politics	Trump, Biden, and Ukraine
28	1.01%	border, southern, secure, senator, illegal	Policy	border and immigration
29	0.66%	farmers, farm, iowa, trade, agriculture	Policy	agriculture
30	1.63%	rights, election, democracy, black, women	Policy	voting and civil rights

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Table B1: Topic Words, Corpus Shares, and Category Codes (continued)

Topic	Share	Top Words	Category	Sub-label
31	0.47%	life, system, pro, behind, reform	Incoherent	–
32	1.78%	forward, look, win, looking, game	Ceremonial	victory words
33	2.96%	fight, fighting, stand, continue, freedom	Ceremonial	generic fighting rhetoric
34	0.58%	million, billion, nearly, program, college	Policy	appropriations
35	1.25%	florida, disaster, recovery, rescue, aid	Policy	disaster relief
36	0.96%	fbi, secretary, role, force, director	Politics	nominations and agency leadership
37	1.38%	gun, violence, lives, save, action	Policy	gun violence
38	3.40%	school, thanks, students, today, meet	Comms	school visits
39	0.82%	gas, chinese, land, oil, national	Policy	public lands
40	0.71%	access, child, rural, leave, using	Policy	rural issues
41	6.36%	want, democrats, people, republicans, get	Politics	generic partisan words
42	1.01%	long, time, pay, get, problem	Policy	equal pay for women
43	0.41%	latest, press, conference, space, sign	Incoherent	–
44	2.77%	tax, big, families, money, americans	Policy	taxes and middle class
45	3.22%	watch, hearing, committee, live, today	Politics	hearings
46	0.47%	texas, north, police, south, mccarthy	Incoherent	–
47	0.26%	union, labor, living, company, raise	Policy	organized labor
48	2.22%	jobs, economy, workers, economic, american	Policy	jobs and economy
49	3.10%	day, years, happy, today, celebrate	Ceremonial	birthdays, holidays, greetings
50	2.18%	care, health, access, affordable, healthcare	Policy	health care
51	1.29%	law, enforcement, policies, officers, police	Policy	law enforcement
52	0.37%	fire, west, virginia, air, army	Incoherent	–
53	2.24%	energy, climate, change, clean, water	Policy	energy and climate
54	0.77%	thousands, young, promise, hundreds, people	Policy	DACA
55	0.42%	find, issues, early, voting, low	Incoherent	–
56	1.99%	education, schools, students, workforce, opportunities	Policy	education and workforce development

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Table B1: Topic Words, Corpus Shares, and Category Codes (continued)

Topic	Share	Top Words	Category	Sub-label
57	3.28%	funding, federal, pandemic, help, resources	Policy	covid and medical funding
58	1.22%	small, businesses, business, irs, credit	Policy	small business
59	0.90%	costs, prices, lower, inflation, vaccine	Policy	drug prices

C Alternative Model Specifications

In Table C1, we test two alternative explanations for our findings: that aligned members spend more time in Washington and post fewer photos of themselves than marginal members who spend more time at home, and that marginal members have more resources and can thus spend more time on photos of themselves. There is no evidence that these alternative theories fully explain our findings.

C.1 Robustness

In Table C2, we refit the all topics fixed effect model in Table 1, column 2, with 40 topics instead of 60. We choose 40 topics for this robustness test given that it had the highest mean coherence score in our grid search, although we qualitatively preferred the topic clusters with 60 topics. The coefficient on co-partisan presidential vote share is essentially unchanged: -0.209 in the main text and -0.217 here, indicating that choosing between these two topic counts does not substantively affect our main result.

In Table C3, we show that our results hold when excluding 2020 (the most intense COVID period), video still, and images from quote tweets and retweets.

C.2 Count Models

Table C4, we re-specify our dependent variable as a count of different types of images. We find that marginal and aligned members post roughly the same number of images of themselves. The shifts in shares that we observe are driven by aligned members posting more of other kinds of images.

C.3 Redistricting Test

In Table C5, we test whether change in district boundaries induced by 2020 redistricting leads to a shift in image composition among lawmakers who served in both the 117th (pre-redistricting) and 118th (post-redistricting) Congresses. This test isolates the discrete change in district alignment resulting from redistricting while holding members and underlying 2020 presidential election fixed. If member-presence in images is driven by

strategic adaptation, we would expect to see a decrease (increase) in the member-present share among lawmakers whose constituencies become more (less) aligned between these two congresses.

Our sample includes 347 House members who served in both Congresses and posted at least one image during both windows. As our data end on July 11, 2023, six months into the 118th Congress, we restrict our analysis in the first window to images posted between January 4 through July 10 2021 (the first six months of the 117th Congress) to match. This restriction limits our dataset, but ensures we are making comparable comparisons across the two periods. We construct first differences by computing the change in the proportion of member-present images across this gap which we regress on the corresponding change in a member's co-partisan presidential vote share, weighting by the sum of images posted across both congresses. The results, which appear in Table C5, provide inconclusive evidence. Directionally, the estimate is consistent with strategic adaptation. Across the redistricting gap, the coefficient is -0.036 . That is, lawmakers whose constituencies become more aligned after redistricting decrease the share of member-present images they post. However, this estimate is not statistically significant. From these estimates, it is difficult to know whether self-presentation is stable across constituency alignment or if we simply lack sufficient variation to draw strong conclusions. These results rely on a single redistricting cycle where the standard deviation in alignment change is just 4 percentage points. Relatedly, the interquartile range is just $[-1.37, 1.40]$. Additionally, it includes only six months of images from each Congress, and in 2021, many were still distancing due to the COVID Delta Variant. Most members experience little change in constituency alignment, and we are hesitant to draw strong conclusions without a longer time series.

Table C1: Member-Presence by Constituency Alignment, Alternative Explanations

	Activities	Resources	
	Voting Days	Campaign Receipts	House Office Accounts
	(1)	(2)	(3)
Co-partisan Pres. Vote Share	-0.229* (0.097)	-0.319** (0.104)	-0.228* (0.095)
Logged Campaign Receipts		0.008* (0.004)	
Female	0.021 (0.013)	0.017 (0.012)	0.013 (0.015)
Senate	0.044** (0.015)	0.057*** (0.015)	
Republican	0.026 (0.015)	-0.002 (0.015)	0.013 (0.016)
Majority	0.014 (0.007)	0.011 (0.007)	0.012 (0.007)
Presidential Co-Partisan	0.018 (0.011)	0.013 (0.008)	0.014 (0.008)
Black	0.006 (0.023)	0.003 (0.022)	0.004 (0.025)
Latino	-0.007 (0.022)	-0.021 (0.017)	-0.015 (0.021)
Past Vote Share	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Leadership	0.022 (0.017)	0.013 (0.017)	-0.007 (0.018)
Seniority	-0.002 (0.002)	-0.003* (0.002)	-0.004* (0.002)
Congress FE	✓	✓	✓
Num.Obs.	549525	2108	1651
R2 Adj.	0.011	0.163	0.139
R2 Within Adj.	0.006	0.109	0.066

Note: Results come from ordinary least squares models. In column 1, the dependent variable is whether an image is member-present. We exclude the House proxy-voting period from May 20, 2020 to January 2, 2023. In columns 2 and 3, variables are the proportion of images in which the member is present by member-Congress, image-weighted. Standard errors are clustered at the member level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table C2: Member-Presence with 40 Topic Fixed Effects

	(1)
Co-partisan Pres. Vote Share	-0.217* (0.085)
Female	0.008 (0.010)
Senate	0.064*** (0.013)
Republican	-0.011 (0.013)
Majority	0.011 (0.006)
Presidential Co-Partisan	-0.003 (0.007)
Black	-0.002 (0.019)
Latino	-0.020 (0.014)
Past Vote Share	0.001 (0.001)
Leadership	0.030* (0.015)
Seniority	-0.003* (0.001)
Congress FE	✓
Topic FE	✓
Num.Obs.	2189441
R2 Adj.	0.086
R2 Within Adj.	0.007

Note: Results come from an ordinary least squares model. The dependent variable is whether an image is member-present. Standard errors are clustered at the member level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table C3: Member-Presence by Constituency Alignment, Robustness

	Excluding 2020	Excluding Video Stills	Excluding QT/RTs
	(1)	(2)	(3)
Co-partisan Pres. Vote Share	-0.345** (0.107)	-0.347*** (0.097)	-0.135* (0.060)
Female	0.017 (0.012)	0.019 (0.012)	-0.008 (0.010)
Senate	0.061*** (0.015)	0.048** (0.016)	0.047*** (0.013)
Republican	-0.001 (0.016)	-0.001 (0.015)	0.017 (0.011)
Majority	0.008 (0.006)	0.011 (0.007)	0.004 (0.006)
Presidential Co-Partisan	0.017 (0.010)	0.019* (0.008)	0.022*** (0.007)
Black	-0.003 (0.022)	0.001 (0.022)	-0.023 (0.018)
Latino	-0.018 (0.018)	-0.022 (0.017)	-0.032 (0.016)
Past Vote Share	0.001 (0.001)	0.001 (0.001)	0.001 (0.000)
Leadership	0.004 (0.018)	0.019 (0.018)	0.031 (0.017)
Seniority	-0.003* (0.002)	-0.004* (0.002)	-0.004** (0.001)
Congress FE	✓	✓	✓
Num.Obs.	2148	2150	2104
R2 Adj.	0.145	0.155	0.135
R2 Within Adj.	0.102	0.095	0.081

Note: Results come from weighted ordinary least squares models estimated on member-congress proportions. The dependent variables are the proportion of images in which the member is present by member-Congress. Observations are weighted by the number of images. Standard errors are clustered at the member level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table C4: Member-Presence by Constituency Alignment, Counts

	Images of Member	Co-Partisan Figures	Out-Party Foil	Other Lawmaker	Unidentified Face	No Detected Face
	(1)	(2)	(3)	(4)	(5)	(6)
Co-partisan Pres. Vote Share	-0.260 (0.390)	4.040*** (0.930)	5.382*** (1.007)	2.957*** (0.661)	0.994 (0.672)	1.187* (0.473)
Female	0.250*** (0.065)	0.122 (0.092)	-0.351** (0.126)	0.198* (0.081)	0.246** (0.076)	0.101 (0.064)
Senate	0.419*** (0.082)	-0.016 (0.116)	0.033 (0.214)	-0.027 (0.112)	0.237* (0.102)	0.140+ (0.082)
Republican	-0.253*** (0.063)	0.178 (0.118)	-0.182 (0.181)	-0.115 (0.097)	-0.216* (0.092)	-0.280*** (0.071)
Majority	0.004 (0.028)	0.354*** (0.047)	-0.634*** (0.054)	0.037 (0.041)	-0.019 (0.033)	0.029 (0.028)
Presidential Co-Partisan	-0.047 (0.036)	0.504*** (0.076)	-1.045*** (0.100)	-0.233*** (0.055)	-0.045 (0.046)	-0.180*** (0.039)
Black	0.075 (0.099)	0.353* (0.179)	-0.186 (0.199)	0.146 (0.132)	0.194 (0.124)	-0.066 (0.107)
Latino	0.174 (0.106)	0.294 (0.197)	0.043 (0.201)	0.213+ (0.129)	0.279* (0.122)	0.241* (0.097)
Past Vote Share	0.001 (0.003)	-0.006 (0.005)	-0.016** (0.006)	-0.008* (0.004)	-0.004 (0.004)	-0.004 (0.003)
Leadership	0.313** (0.101)	0.447*** (0.124)	0.638** (0.219)	0.784*** (0.208)	0.196+ (0.109)	0.205+ (0.108)
Seniority	-0.043*** (0.008)	-0.030** (0.011)	-0.015 (0.027)	-0.027** (0.009)	-0.043*** (0.009)	-0.025** (0.008)
Congress FE	✓	✓	✓	✓	✓	✓
Num.Obs.	2150	2150	2150	2150	2150	2150
R2 Adj.	0.021	0.047	0.047	0.035	0.029	0.034
R2 Within Adj.	0.009	0.025	0.034	0.016	0.009	0.010

Note: Results come from negative binomial models estimated on member-congress counts. The dependent variables are the counts of images as specified in the table. Standard errors are clustered at the member level. $^+p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table C5: Change in Image Composition After 2020 Redistricting

	(1)
Change in Alignment (118 - 117)	-0.036 (0.177)
Baseline	0.147*** (0.007)
Num.Obs.	347
R2 Adj.	-0.003

Note: Results come from ordinary least squares models estimated on member-congress proportions. The dependent variable is the change in the share of member-present images. We weight by the sum of images posted in both congresses. Standard errors are clustered at the state level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.