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The Role of Personal Availability and Gender in Negative Online Congressional Campaigning

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Abstract
Negative campaigning in elections has received considerable attention. However, an important dimension of negative campaigning remains underexplored: the extent to which a candidate's presentation of self affects their likelihood of *receiving* negativity. Work on gender differences in self-personalization and media personalization also suggests that this effect might be shaped by candidate gender. This paper investigates if a candidate using personal details in the service of campaign promotion increases the likelihood that the candidate will receive negativity from an opponent and if this association is moderated by candidate gender. Using congressional campaign website data from 2002 to 2006, evidence does not suggest that candidates who personalize online are any more likely to receive online negativity. Further, findings suggest that only female candidates see their likelihood of receiving online negativity vary as a function of online self-personalization. Female candidates have a higher likelihood of receiving online negativity from their campaign opponent when the candidate is more personable—that is, when they make information about their private selves more publicly available for negative framing at the hands of their opponent. Robustness checks reveal that this effect is not time independent, however, suggesting the personalization-gender-negativity relationship may be conditional on electoral context. Implications for work on personalization and negative campaigning, the role of gender in these processes, and campaign risk-taking are discussed.

Keywords Negative campaigning · Online campaigning · Content analysis · Gender · Impression formation · Personalization

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Introduction

Negative campaigning in elections has received considerable attention, comprising a sizeable literature in political science (Lau & Rovner, 2009). Research on negative campaigning—i.e., "any criticism leveled by one candidate against another during a campaign" (Geer, 2008, p. 23, as cited in Krupnikov, 2011, p. 798)—has illustrated that a range of structural and contextual factors influence the likelihood a candidate will receive negativity from an opponent, both in traditional and "new" forms of political communication (Druckman et al., 2010b). Importantly, elements of a candidate's political identity—such as the type of political discourse they engage in and their partisan affiliation—predict whether or not a candidate uses negativity as a campaign strategy (e.g., Druckman et al., 2010b; Elmelund-Præstekær, 2011). However, given that persuasion in American politics has deep referential anchors in personal life (Lakoff, 2010) and the increasing "personalization" of political discourse (Stanyer, 2013; van Zoonen, 2005), could it be that a candidate's use of personal information may also be linked to the likelihood of their being the target of negative campaigning? Further, with evidence suggesting that online personalization plays out differently depending on whether the candidate is male or female (McGregor, 2018; Meeks, 2017), does personal availability have differential associations with receiving negativity depending on the candidate's gender?

I assess these two questions in this paper. First, I examine whether a candidate's presentation of self—net of explicitly political details—predicts whether their opponent will lob negativity their way, specifically on the candidates' official campaign websites. I then assess if personal availability has differential associations with online negativity reception depending on the candidate's gender.

Candidates who make information about their personal self publicly available may provide their opposition more information with which to partake in negative framing—i.e., the attempt to control the assemblage of the candidate's public political presence. While being personable and approachable may benefit a political candidate, personability may be a double-edged sword insofar as it provides access to information from which their opponent can play an active hand in the framing or reframing of the candidate's political identity. However, this association may be particularly pronounced for women. Female candidates—like their male counterparts—engage in personalization strategies in order to reap the benefits that they offer in terms of constituent evaluation; and yet, female candidates are often framed in media discourse by their personal characteristics rather than their political acumen and policy knowledge. This double bind creates a situation wherein female candidates must make themselves more personable online to increase positive voter perceptions while also making "personalization affordances" (McGregor et al., 2017, p. 266) to their campaign opposition for negative framing.

This paper proceeds as follows. I first present the theoretical framework, which draws on work in cultural sociology and cognitive psychology on availability, work in social psychology on impression formation, and work in political science on gender differences in personalization to construct an account of why candidate personability may increase the chances of receiving opponent negativity and how this association might be moderated by candidate gender. Second, I briefly overview existing work on negative campaigning in order to synthesize other potential explanations. Third, I detail the data used here—the results of a content analysis of U.S. congressional campaign websites from 2002 to 2006 (Druckman et al., 2013)—and the analytical strategy. After reporting the results, I then present a robustness check to assess stability of the personalization-gender-negativity relationship over time. I conclude with some implications for work on the personalization of political discourse in the U.S. context, campaign risk-taking, and the role of gender in these processes.

Availability, Impression Formation, and Gender

The Availability Heuristic

An account for why the amount of personal information a candidate puts into the public sphere might increase the likelihood of them receiving negativity from a campaign opponent begins with the notion of *availability*. In order for new information (such as a campaign message) to persuade a person one way or another, they must be able to access it (Schudson, 1989, pp. 160–161). Information is more “available” to the extent that it is easy to call forth into working memory. Information can be more available to a person if they frequently encounter similar types of information, or if the information is more salient in their life experiences. In other words, information is readily available when it is “physically available and[/or] cognitively memorable” (1989, p. 163).

People use availability as a heuristic for making decisions and passing judgments (Pachur et al., 2012; Tversky & Kahneman, 1973, 1974). When it comes to political campaigning, strategists may attempt to leverage this sort of information-processing shortcut by drawing attention to the most publicly salient “bits” of information that accentuate the positive qualities of their candidate and the negative qualities of their opponent. For the strategist, when it comes to the negative characteristics of the rival candidate, the two questions are: What information about the opponent is most culturally available to a general public audience, and why is drawing attention to more culturally available information important for persuading audiences on the opponent’s inefficiencies, shortcomings, or flaws?

Impression Formation Via Personal Availability

A candidate’s political identity provides culturally available information for their opponent to work with. A candidate’s stances on issues salient to the public and their party ideology, for instance, are highly available (i.e., it is less difficult for a politically-engaged audience to recall what these things are and their significance).

But there is another pool of information that is also culturally available to the general public audience: a candidate's *personal* identity.

Following work on impression formation in social psychology, people construct initial judgments of others based not only on the latter's idiosyncratic characteristics, but also on their perceived categories of social belonging (Fiske & Neuberg, 1990; Gawronski et al., 2003; Higgins et al., 1977). For example, a person might be more likely to infer that a man speaking loudly at a company meeting is passionate about their work, while a woman in an otherwise identical context might be judged as emotional. While ascribed characteristics such as (perceived) sex and race are some of the most explicit social categories for impression formation, another set of personal features is details about the candidate's life experiences. This sort of information may include details on the candidate's hometown, their prior non-political work experience, their family life, etc. The fact that these life experiences are so available to a general audience is what makes them useful for positive campaigning: regular, everyday people have hometowns, go to work, and have families. What is more, detailing one's personal life outside of politics might function as a type of "relational messaging" (Pfau & Rang, 1991, p. 116) that promotes an impression of warmth for the audience. This is a particularly prominent strategy in U.S. campaigning, since "elected representatives cannot rely on party loyalties, and so their websites do not project an overt party identity but, instead, focus on projecting personal qualities and establishing a persona that resonates with the local electorate and ensures support" (Stanyer, 2008, p. 428). Personalization may also be an increasingly common strategy on social and digital media platforms as well. A recent study, for example, found that approximately 29% of 2012 House candidates' tweets focused on personal details (Evans et al., 2014, p. 457).[1]

At the same time, this personal availability might be spun by an opponent to show that the candidate is *not* like their constituency and cannot adequately represent them. Going personal could be considered a risky strategy (Druckman et al., 2009). The difference in valence attached to personal availability is largely a function of who is attempting to use it: the candidate or their opponent.[2] A candidate self-personalizing online can be a resource for political opponents to negatively frame the candidate and thereby activate schemas in constituents' minds that lead them to perceiving the candidate as unfit or untrustworthy for public office (Wood et al., 2018).

Taken together, while being more forthcoming with personal information might benefit the candidate in some capacities, it might not always work in the candidate's favor: in the hands of their opponent, the cultural availability of this sort of personal information might be spun to show that the candidate is, e.g., distant,

[1] It is worth noting, however, that evidence of the extent to which candidates are using their social and digital media platforms more for personalizing strategies than for traditional campaign content is mixed (McGregor et al., 2017, pp. 266–267).

[2] As Kahn (1996, p. 53) notes in the context of how voters perceive candidates: "If voters are provided with a great deal of information about a candidates' personality characteristics, then voters are likely to consider this information when developing impressions of candidates." Such is also the case with campaign opponents, with the added threat that opponents can then spin this information in their own constituent messaging strategies.

over-privileged, inexperienced, or inauthentic. In a word, the propensity to be more personally available might lend itself to negative campaigning from their opponent. This motivates the first hypothesis:

Hypothesis #1 Congressional candidates who provide more personal information on their official campaign website are more likely to receive negativity from their campaign opponent.

Gender Differences in Personalization and Its Effects

Are certain candidates more likely to face opponent negativity when they go personal on their campaign website than others? I posit candidate gender is one such moderator. Namely, I suggest that the relationship between personalization and negativity reception may function differently between male and female candidates.

The literature points to two main ways in which gender enters the discussion of personalization in American electoral politics: how *media personalization* is a gendered exercise in journalistic coverage and how the effects of a candidate's *self-personalization* vary between male and female candidates. Each of these dimensions is relevant for the argument at hand.

First, content analyses of media coverage of electoral campaigns show striking consistencies in how male and female candidates are differentially framed. Journalists are more likely to discuss personal attributes of female candidates—e.g., their family life and appearance—and more likely to discuss male candidates in terms of their policies and where they stand on issues (e.g., Aday & Devitt, 2001; Miller & Peake, 2013). Journalists are also more likely to cover male candidates in ways that echo how the candidate frames themselves in campaign ads while female candidates are subject to "weaker correspondence" between how they frame themselves and how the media report on them (Kahn & Fridkin, 1996, pp. 41–42). Media coverage is more likely to focus on a female candidate's (usually negative) viability for winning an election (Kahn & Goldenberg, 1991)—drawing attention to the "character issue" (Braden, 1996, p. 105)—and more likely to lead to poor public opinion about the candidate (Kahn, 1994; Miller & Peake, 2013). In short, media coverage tends to personalize female candidates more than male candidates, and this sort of coverage can lead to more negative evaluations of the female candidate (but see Fridkin and Kenney [2014] for a more nuanced take on how sex stereotypes can be differentially leveraged by female candidates).

Despite the difficulties that female candidates face with media personalization, there are documented benefits to self-personalization—that is, the act of making oneself more personable on the campaign trail with ads, personal details on websites, and so on. Digital political communication is particularly conducive to reaping these benefits. Self-personalization on Twitter, for example, can positively impact voter intention by increasing the sense that there is an intimate connection between the candidate and voter despite the fact that the communication is digitally-mediated (Lee & Oh, 2012; McGregor, 2018). More emotional and private personalized Facebook posts may also promote more audience engagement on the platform in the form of likes, emojis, shares, and comments (Metz et al., 2020). Evidence also suggests that self-personalization on Twitter positively affects perceptions of likeability and competency (Meeks, 2017).

That said, the effects of self-personalization in the digital sphere may be gendered (McGregor, 2018, pp. 1151–1152). Evidence suggests that male candidates who self-personalize on Twitter are more likely than female candidates who self-personalize to be seen as competent when it comes to the economy, healthcare, and national security (Meeks, 2017, p. 20)—three issue domains that are among the most publicly salient across time according to public opinion data (Druckman et al., 2010a, p. 9). Nonetheless, female candidates are more likely to have Twitter accounts (Evans et al., 2014) and more likely to value social media as a campaigning strategy (Sandberg & Öhberg, 2017). Tellingly, despite the interest among female candidates in online campaigning, male candidates appear more likely to self-personalize on Twitter and Facebook (McGregor et al., 2017)—perhaps a result of female candidates being simultaneously aware of the utility of self-personalization and its gendered consequences. There is still incentive for female candidates to self-personalize, however: women who personalize are still seen as more competent than men and women who don't personalize (Meeks, 2017), and women may still foster perceptions of closeness and familiarity with voters who share the same political party identification (McGregor, 2018).

The confluence of these two types of personalization leads to a catch-22: female candidates might see strategic value in online self-personalization for forming voter connections, but the "threat" of media personalization—wherein female candidates are over-personalized and subjected to questions of viability and character—is always present when personal details are "put out there" for consumption. Perhaps even more so than the media, female candidates' campaign opponents have a vested interest in painting the candidate in the negative.

This leads to the second hypothesis:

Hypothesis #2 Female congressional candidates who provide more personal information on their official campaign websites are more likely to receive negativity from their campaign opponent than male congressional candidates.

Methods

Data

I use the Congressional Candidate Websites dataset, archived at the Inter-University Consortium for Political and Social Research (ICPSR 34895; (Druckman et al., 2013)). The data are from a quantitative content analysis of United States Senate and House candidate campaign websites during the 2002, 2004, and 2006 election cycles. The unit of analysis is the individual candidate in an individual race (overall $N = 736$), and the data consist of all major party candidates for Senate seats and a 20% random sample of House candidates stratified by state and district (Druckman et al., 2010b, p. 92).[3] The N for the analytical sample was 690 campaigns nested within 604 candidates after listwise deletion across the variables described below.[4] Political independents were removed from the sample due to small sample size.

This study tests the above theoretical framework using website campaigning data and can perhaps only be generalized strictly to online campaigning. However, the determinants of going negative do not vary substantially between the web and more traditional campaign outlets (Druckman et al., 2009, 2010b; Schweitzer, 2005, 2011).[5] Extending the findings outlined here to negative campaigning more generally is not wholly inappropriate.

It is also worth addressing the potential concern that these website data are from 2002 to 2006—some time ago when considering how fast mass communication technologies change. Can we be confident that findings from these data might still hold in election cycles today? Evidence suggests that we can: by and large, how U.S. candidates' teams view the utility of websites as a campaigning platform is fairly consistent across time, including the 2016 general election in all of its idiosyncrasies (Druckman et al., 2018a. b). Moreover, while social media has become entrenched in the online campaigning repertoire in recent election cycles, campaign strategists as recently as the 2016 presidential election continue to view and use official campaign websites as "repositories of information"—or "digital hubs"—that are better than social media for conveying their messages to generalist audiences (Druckman et al., 2018b, p. 399). This means that although these data are from 2002 to 2006, there is little empirical evidence to suggest that the rise of social media in later years would greatly affect estimates of how campaigns use their websites now.[6]

Measures

The variables used in the analysis are outlined below, including variables for other structural and contextual factors known to predict going negative. Descriptive statistics for all variables are presented in Table 1.

[3] Concerning selection biases in terms of candidates having personal campaign websites, Druckman and colleagues note that "[they] were able to identify almost all Senate candidate Web sites and nearly 95% of House sites in ...[the] sample. This suggests that while not all candidates had Web sites, clearly the overwhelming majority did" (2010b, p. 92).

[4] More information on the data collection procedure can be found in Druckman et al. (2010b, pp. 92–93).

[5] Indeed, though politically involved or engaged actors are more likely to visit campaign websites, "voters in general" and "undecided voters" remain the "primary target audiences" on these web platforms (Druckman et al., 2009, p. 346; Druckman et al., 2010b). For instance, there is a strong association between levels and likelihoods of negativity in both website- and television-based campaigning. As Druckman and colleagues note: "Forty-eight percent (351 of 732) of candidates went negative on the Web, compared to 55% in their television advertisements (128 of 232). Candidates are not more likely to go negative on the Web" (2010b, p. 95).

[6] It is interesting to note, however, that campaign strategists reported going negative less often on their websites for the 2016 election cycle than they did from 2008 to 2014 election cycles (Druckman et al., 2018b, p. 400).

Table 1 Descriptive statistics for all variables

Variable	Mean	SD	Min	25%	Median	75%	Max
Received negativity (0 = No, 1 = Yes)	0.46	–	0	–	–	–	1
Personal availability (sd)	0	1	− 1.90	− 0.87	− 0.02	0.88	1.85
Gender (0 = Male, 1 = Female)	0.18	–	0	–	–	–	1
Went negative (0 = No, 1 = Yes)	0.49	–	0	–	–	–	1
Issue ownership (sd)	0	1	− 2.29	− 0.79	0.02	0.79	2.47
Issue salience (%)	13.23	7.41	0	8.05	11.97	17.17	50.50
Competitiveness	0.24	0.38	0	0	0	0.67	1
Status (0 = Not a Challenger, 1 = Challenger)	0.42	–	0	–	–	–	1
Chamber (0 = House, 1 = Senate)	0.27	–	0	–	–	–	1
Party (0 = Rep, 1 = Dem)	0.48	–	0	–	–	–	1
Open seat (0 = No, 1 = Yes)	0.14	–	0	–	–	–	1
Race (0 = White, 1 = Non-white)	0.07	–	0	–	–	–	1
District/State population (in 1000s)	1985.61	3794.29	493.78	635.50	654.36	783.60	33871.65
% of district/state with H.S. diploma or higher	82.11	5.65	50.40	79.40	83.30	86.10	95.60
Median family inc in district/state in 1999 (in $)	51210.01	10799.27	30413.00	43654.00	49413.50	56695.00	91249.00
Fundraising (in $)	2,275,243	3,594,662	0	354,044	1,087,664	2,313,168	39,612,763
Negativity in national politics (0 = No, 1 = Yes)	0.32	–	0	–	–	–	1
Year, 2002	0.23	–	–	–	–	–	–
Year, 2004	0.35	–	–	–	–	–	–
Year, 2006	0.41	–	–	–	–	–	–
Personal Availability Observables							
Family bio details (0 = No, 1 = Yes)	0.47	–	0	–	–	–	1
Town bio details (0 = No, 1 = Yes)	0.63	–	0	–	–	–	1
Other job bio details (0 = No, 1 = Yes)	0.83	–	0	–	–	–	1
Membership bio details (0 = No, 1 = Yes)	0.50	–	0	–	–	–	1

Table 1 (continued)

Variable	Mean	SD	Min	25%	Median	75%	Max
Volunteering bio details (0 = No, 1 = Yes)	0.30	–	0	–	–	–	1
Military bio details (0 = No, 1 = Yes)	0.23	–	0	–	–	–	1

$N = 690$ for all variables. The "fundraising" variable is logged in the regression analyses but is reported in U.S. dollars here

Outcome Variable: Negativity Reception

The outcome variable in the analysis is a dichotomous measure capturing whether or not a candidate's opponent went negative (0 = opponent did not go negative; 1 = opponent did go negative) in a given race. The content or reason for the negativity may have been personal, issue/platform-based, both, or other (Druckman et al., 2013, p. 6). According to Druckman and colleagues (2010b, p. 92):

> Coders examined all major parts of the candidate's self-contained Web site for evidence of negativity. That is, they searched the homepage, the fundraising area, the issues area, the biography area, and any other major area linked to the homepage (e.g., news room and media pages) to find material about the candidate's opponent that was negative or critical—either in tone or explicitly.

A candidate was coded as "going negative" if they mentioned the opponent explicitly by name or with a general descriptor such as "my opponent" (Druckman personal communication, January 17, 2020).

The dataset also provides a measure for whether or not the candidate lobbed specifically *personal* negativity at their opponent. Appendix 4 provides details on why this measure was not used to create the dependent variable for this study.

Independent Variable #1: Personal Availability

The first of two main predictor variables is a measure of the extent to which any candidate provides online information about themselves outside of their role as a political actor. Multiple correspondence analysis (MCA) was used to obtain this measure from a matrix of six dichotomous variables (Greenacre & Blasius, 2006; Lizardo & Taylor, 2020).[7] MCA is a form of matrix factorization for categorical variables. Specifically, MCA applies singular value decomposition (SVD) to a candidate-by-variable-category indicator matrix where each *ij* cell is normalized to be the square root of that cell's contribution to the matrix's χ^2 test statistic. The goal of the matrix factorization is to return a set of latent components with a lower dimensionality than the original matrix, but which maximize the variance in that matrix. Each consecutive dimension accounts for less of the total variance—or, in MCA terminology, the "total inertia," $\frac{\chi^2}{n}$—in the original matrix. In other words, dimension #1 accounts for most of the variance, dimension #2 the second most, etc.

MCA returns a set of component scores that represent how the row and column elements are distributed across the dimensions. These scores (one per dimension) are on a continuous scale and are represented as a vector of *principal coordinates*:

[7] Results from the estimated regression models were similar when constructing this variable using principal components analysis and as a simple additive index. Cronbach's alpha for the six-item additive scale was low ($\alpha = .36$), which might reflect the fact that the underlying factor space between these six items is a higher dimensional one. The first two dimensions of the PCA space, for example, each have eigenvalues greater than one, and the second dimension in the MCA space accounts for a non-trivial 18% of the total inertia ($\frac{\chi^2}{n}$) in the indicator matrix.

$$C_x = \frac{U \times \sqrt{\lambda}}{\sqrt{\sum f_x/_N}} \tag{1}$$

where x is either a row or a column, U is the matrix of row eigenvectors from the SVD, λ is the eigenvalue corresponding to that dimension (and $\sqrt{\lambda}$ is known as the "singular value"), f_x is the frequency of x in a given cell in the row/column vector, and N is the total number of cases (candidates) in the matrix (Kassambara, 2017). Each candidate's coordinates can be roughly interpreted as the correlation between their row profile across the six observed variables and the underlying dimension.

The variables in the indicator matrix reflect the extent to which the candidate includes personal information on their official campaign website. These variables are treated here as *indicators of* a more general propensity of the candidate to be more personally forthcoming on the campaign trail. The variables are all dichotomous, where 0 = no and 1 = yes. "Family" indicates whether or not the website contains details about the candidate's family. "Town" indicates whether or not the candidate provides information being from (or growing up in) the district/state. "Organization" indicates whether or not the candidate specifies if they are members of any organization. "Volunteer" indicates whether or not the candidate specifies if they have served as a volunteer in some capacity. Finally, "Veteran" indicates whether or not the candidate mentions any military service.

The question is whether or not one of the dimensions can be interpreted as a measure of the extent to which the candidate provides non-political/personal information about themselves. Figure 1 arrays the variable categories along the first two dimensions in a two-dimensional Euclidean subspace (a hallmark of MCA). Dimension #1—which accounts for about 26.83% of the variance in the original indicator matrix— partitions the categories by 0 s (left) and 1 s (right). The first dimension, then, appears to pick up on a "personal availability" point of distinction: i.e., the extent to which a candidate puts their personal information "out there" on their campaign website and available for oppositional framing.

Principal coordinates for this dimension were extracted.[8] Positive and larger values indicate a candidate (in a particular race) who is more prone to making personal information public; the reverse is true for negative and larger values. The variable was then standardized prior to use in the regression analyses.

Independent Variable #2: Candidate Gender

The second main predictor was the candidate's gender, measured as a dichotomous variable, where 0 = male and 1 = female.

[8] Multiple correspondence analyses were carried out using the `FactoMineR` package (Husson et al., 2013) in the R statistical computing environment (Team et al., 2013). All visualizations in this paper were made using `ggplot2` (Wickham, 2016).

Other Predictors of Negative (Online) Campaigning

There are documented differences in the likelihood that a candidate will go negative (both in traditional outlets and online) depending on candidate and campaign characteristics that may also be relevant for exploring when a candidate *receives* negativity. Challengers are more likely to go negative during congressional campaigns than their incumbent counterparts (Schweitzer, 2011, p. 323; Trammell, 2006, p. 404)—including on their campaign websites (Druckman et al., 2018b)—though this negativity gap shrinks as races become more competitive (see also Druckman et al., 2009). This finding implies that, though it behooves current seat holders to remain generally silent given their "risk averse" nature (Milita et al., 2014, p. 446), the move towards negativity becomes more of an option for incumbents when it is unclear how the race will turn out (see also de Nooy & Kleinnijenhuis, 2013, p. 133). Open seat candidates—i.e., candidates running for a seat without an opposing incumbent—are also more likely to go negative that non-open seat candidates; though, once again, this negativity gap grows smaller as races become more competitive (Druckman et al., 2010b).[9] The likelihood of going negative also rises as candidate funds increase (likely because these candidates can afford the materials and staff necessary for going negative effectively and strategically), and the likelihood also increases for Democrats, female candidates, and Senate races in the online case (Druckman et al., 2010b). Going negative as a response to an opponent going negative (that is, as a response to receiving negativity), remains insignificant on Web-based platforms, unlike in television advertisements (Druckman et al., 2010b).

Additionally, research in the Danish context suggests that candidates are more likely to go negative when they have low "issue ownership": i.e., when they engage issues that their party is not perceived to "own" in the public sphere (Elmelund-Præstekær, 2011). Findings from the U.S. context are conflicting: candidates are more likely to go negative in advertisements when their party owns the discussed issue (Damore, 2002). Similarly, U.S. candidates are more likely to go negative in an advertisement when the issue centered in the communication is considered salient in the public sphere (Damore, 2002).

Control variables for each of these factors are included, given that the same candidate and campaign characteristics that influence the likelihood of going negative should exert similar (but reversed) influences on the likelihood of receiving negativity. Specifically, the following variables were adjusted for in all of the statistical models: challenger status (0 = not a challenger; 1 = challenger); open seat status (0 = not an open seat; 1 = open seat); a competitiveness score[10]; an interaction between

[9] Though Druckman et al. (2010b) found that candidates were much more likely to go negative in their online campaigning in highly competitive races. However, in their study of negative campaigning in Senate races from 1988 to 1998, Lau and Pomper (2001) found that the competitiveness of a race was not a significant predictor of going negative after adjusting for other factors.

[10] Competitiveness was measured using *The Cook Political Report* (Druckman et al., 2010a, p. 347). Race competition ratings from these reports were used to classify each race according to whether it was "solid Democratic or Republican" (0), "likely Democratic or Republican" (.33), leaning Democratic or Republican" (.67), or a "toss-up" (1).

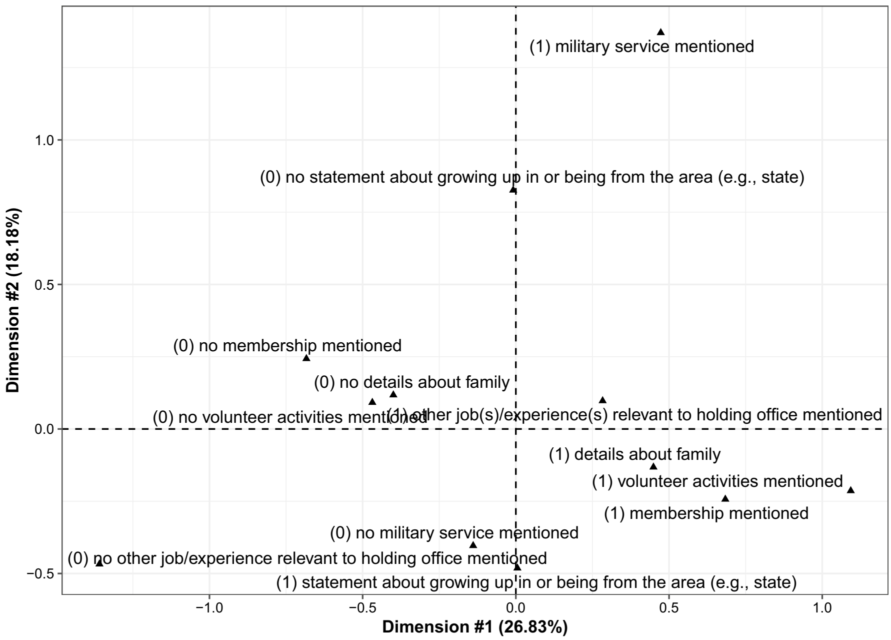

Fig. 1 MCA Mapping of Dimensions #1 and #2 for Independent Variable. *Note* Dimension #1 is standardized prior to using in the regression analyses. Dimensions #1 and #2 together account for about 45.01% of the total inertia (that is, total variance) of the original candidate-by-variable-category indicator matrix. The variable category labels are plotted at their respective coordinates (found via Eq. [1]) in the MCA factor space along the first two dimensions

the competitiveness score and each of the challenger and open seat status variables to account for the documented nonlinear effects between these variables on the likelihood of going negative; party affiliation (0 = Republican; 1 = Democrat); chamber (0 = House of Representatives; 1 = Senate); fundraising in U.S. dollars (logged)[11]; and a binary variable indicating whether or not the candidate themselves went negative toward their opponent on the website (where, like the dependent variable, the negativity could be personal, issue-based, both, or other). To account for the possibility that a candidate is more likely to receive negativity if they themselves go negative against high-status political figures, I include a binary variable indicating whether or not the candidate went negative against W. Bush (2004 or 2006), Cheney (2006), Kerry (2004), or either of the two major political parties (2006). Finally, issue ownership and issue salience are incorporated into the models using measures computed by Druckman et al. (2009, p. 349;, 2010a, p. 9).[12] The ownership

[11] The dataset also includes a measure of funds spend in U.S. dollars. However, there is a high bivariate correlation between the funds received and funds spent variables in the full sample ($r = 0.987$). As such, only the funds received variable is used in the analyses.

[12] The issues addressed on each candidate's website were coded and organized into the following higher-order typology: defense, jobs and the economy, healthcare, education, group advocacy, environment, government reform, immigration, crime, moral/ethical issues, social security, taxes, and govern-

variable was standardized prior to analysis and interacted with the salience variable to account for the possibility that, if an issue is deemed important enough, a candidate might feel obliged to take on the issue even if their party is not perceived to "own" it (Druckman et al., 2010a)—thereby making the candidate susceptible to opponent negativity when they attempt to address the issue.

I also adjust for the candidate's race-ethnicity (0 = white; 1 = nonwhite) and a series of sociodemographic variables—since it is plausible that the likelihood of a candidate receiving negativity from their opponent candidate varies depending on characteristics of the district/state to which the candidates are ostensibly attempting to appeal with their online presentations of self. These sociodemographic predictors are district (for House candidates) or state (for Senate candidates) population size (per 1,000), district/state education level (measured as the percent of the district with a high school diploma or higher), and district/state median family income in 1999 (measured in U.S. dollars). Year fixed effects are included with 2004 as the reference category.

Estimation Strategy

I used probit regression to assess the research hypotheses.[13] Two primary models are reported: an additive model with personal availability as the main independent variable (testing hypothesis #1) and a multiplicative model with an interaction between personal availability and candidate gender (testing hypothesis #2).[14]

Footnote 12 (continued)
ment spending (Druckman et al., 2010a, p. 9). These data were then compared to national public opinion polls to create "issue ownership" scores for each issue area. These scores were the estimated percent of the public who believed an issue was "owned" by Republicans or Democrats in that year. These issue scores were then summed per candidate depending on how many times they brought up a particular issue on their website. Each issue score in the summation was also signed according to the candidate's party affiliation (where, e.g., a Democratic candidate gets a + for an issue they address that is owned more by Democrats and a - for an issue that is owned more by Republicans). The summation was then normalized by the total number of issues brought up on the candidate's website. The resulting "Issue Ownership" variable reflects the extent to which a candidate in a given race addresses issues more associated with their party, where larger and more positive values indicate more party-aligned issue engagement and more negative values indicate less party-aligned issue engagement (Druckman et al., 2009, p. 349). To index issue salience, each issue area per year was scored as the percent of the public (in that year) that saw that issue area as one of the two most important issues facing the country using public opinion data on issue importance derived from Harris Interactive (Druckman et al., 2009, p. 361). These percentages were then summed for each candidate in a race depending on the number of times the candidate engaged the issue on the site and normalized by the number of issues discussed (Druckman et al., 2009, p. 361). The resulting "Issue Salience" variable is the mean public importance (in %) of the issues addressed by the candidate in that year.

13 Logit models give similar results to the probit models.

14 A random effects probit model with campaigns nested within candidates produced virtually identical results to the one-level probit model for the primary coefficients of interest. Lastly, to account for the possibility that the associations of interest here are primarily candidate-level associations rather campaign-level associations, I ran a linear between-effects model—where the proportion of a candidate's total campaigns wherein they received negativity is regressed on candidate-level means for all covariates. The main coefficients of interest are the same in terms of direction, though the effect size is slightly attenuated when compared to the one-level probit model. However, an unconditional variance decompo-

Potential limitations with this assumed unidirectional probit estimation strategy—namely, the issue with possible reciprocal causation between negativity reception and personalization—are addressed in the concluding section of this paper.

Results

Primary Models

The results from the probit models are presented as a coefficient plot in Fig. 2. The points are the probit coefficients and the error bars are 95% confidence intervals. As such, any confidence interval that does not include 0 indicates a statistically significant association at at least $\alpha = 0.05$ (two-tailed). The models in table form are in Tables 4 of Appendix 1.

The model 1 estimates are presented in orange. The personal availability coefficient is positive ($\hat{\beta} = 0.005$) but not a statistically significant predictor of a candidate in a particular congressional race receiving negativity. Hypothesis #1, then, does not find empirical support. There is insufficient evidence to suggest that negativity reception varies as a function of the extent to which the candidate makes themselves more personally available on their official campaign websites, net of other factors.

The results for model 2—testing the second hypothesis—are in blue.[15]

Looking at model 2, while a candidate's propensity to receive negativity does not appear to vary as an additive function of their personal availability during the campaign in question, this association is moderated by the candidate's gender. While the personal availability slope is not statistically significant for male candidates ($\hat{\beta}_{Availability|Male} = -0.047$; $z = -0.775$), and the gender gap is also not statistically significant for candidates with a mean personal availability score ($\hat{\beta}_{Female-Male} = -0.059$; $z = -0.378$), the association between negativity reception and personal availability is significantly different between male and female candidates. While the availability slope for male candidates is -0.047, the availability slope for female candidates is 0.262 (0.309–0.047; $z = 1.787$); importantly, the z-test for the interaction term itself suggests that the availability slopes, conditional on gender, are significantly different from one another ($\hat{\beta}_{Availability \times Female} = 0.309$; $z = 1.979$). More availability appears to be positively associated with a higher likelihood to receive opponent negativity, but only for female candidates. The interaction term provides a modest improvement to model fit relative to model 1, as indicated by a likelihood

Footnote 14 (continued)
sition probit model (Singer et al., 2003, p. 75) suggested that very little of the total variance in the negativity reception variable is accounted for at the candidate level—about 10%. Taken together, a simple one-level probit model was chosen over random effects and between effects specifications. These multilevel results are available upon request.

[15] A version of the model with constituency fixed effects—states for Senate candidates and state districts for House candidates—provided similar coefficient estimates. The model fit, however, was poorer with constituency fixed effects ($AIC_c = 796.761$ and $BIC = 1345.944$, though $AIC = 625.761$) when compared with the reported model (see Table 2). This was also the case for the model 1.

ratio chi-square test ($\chi^2 = 4.406$; $p = 0.036$) reported in Table 2. Two of three standard information criteria also suggest adding the interaction term (moderately) improves model fit: $\Delta AIC_{a-m} = 2.406$ and $\Delta AIC_{c_{a-m}} = 2.265$,[16] where a indexes the additive model (model 1) and m indexes the multiplicative model (model 2).[17] Collectively, this provided support for hypothesis #2.

Back-transformed predicted probabilities help illustrate the magnitude of these associations from model 2; they are reported in Fig. 3, panel A (panels B and C are addressed in the discussion section). After adjusting for other factors, a male candidate with average levels of personal availability on their campaign website has approximately a 57% chance of receiving negativity while an otherwise identical female candidate has about a 54% chance. However, when the personal availability score is one standard deviation above the mean, a male candidate has about a 55% of receiving negativity and a female candidate about a 64% chance (all else equal). The overall effect of personal availability for male candidates on the predicted probabilities for negativity reception is both small, negative, and not statistically significant, as shown in the average marginal effect reported in Table 3 ($AME_{male} = -0.019$; $z = -0.734$). The opposite is the case for female candidates: the average marginal effect is larger, positive, and statistically significant ($AME_{female} = 0.100$; $z = 2.029$). A series of Wald tests suggest that the differences in predicted probabilities *between* male and female candidates are not significantly different from one another at the various personal availability scores; however, as both the model coefficients and marginal effects show, the general trend lines nonetheless suggest a positive association between negativity reception and personalization for female candidates and virtually no association for male candidates.

A few of the control variables are statistically significant predictors of negativity reception in model 2. Challengers are less likely to receive negativity when they are in very noncompetitive races ($\hat{\beta}_{Challenger-Incumbent} = -0.928$; $z = -4.332$). This finding is consistent with the literature on negative political campaigning, which finds that incumbents are less likely to lob negativity when there is high confidence in the outcome of a race (Druckman et al., 2010b; Schweitzer, 2011; Trammell, 2006). High fundraisers are also more likely to receive negativity ($\hat{\beta}_{Fundraising} = 0.255$; $z = 4.355$), and candidates in 2002 races were less likely to receive negativity than their 2004 counterparts ($\hat{\beta}_{2004-2002} = -0.466$; $z = -2.947$). More competitive races are also associated with higher propensities to receive negativity when the candidate is an incumbent ($\hat{\beta}_{Compete|Incumbent} = 0.819$; $z = 2.712$).

[16] The AIC_c statistic—a version of AIC that adjusts for the tendency of AIC to suggest overfitting models in the presence of small sample sizes (Hurvich & Tsai, 1989)—was calculated as follows for each model: $AIC_c = AIC + \frac{2k(k+1)}{n-k-1}$, where k is the number of estimated parameters (including the intercept) and n is the sample size (Burnham & Anderson, 2003, p. 66).

[17] The ΔBIC_{a-m} does not suggest any sort of meaningful increase in model fit ($\Delta BIC_{a-m} = -2.131$).

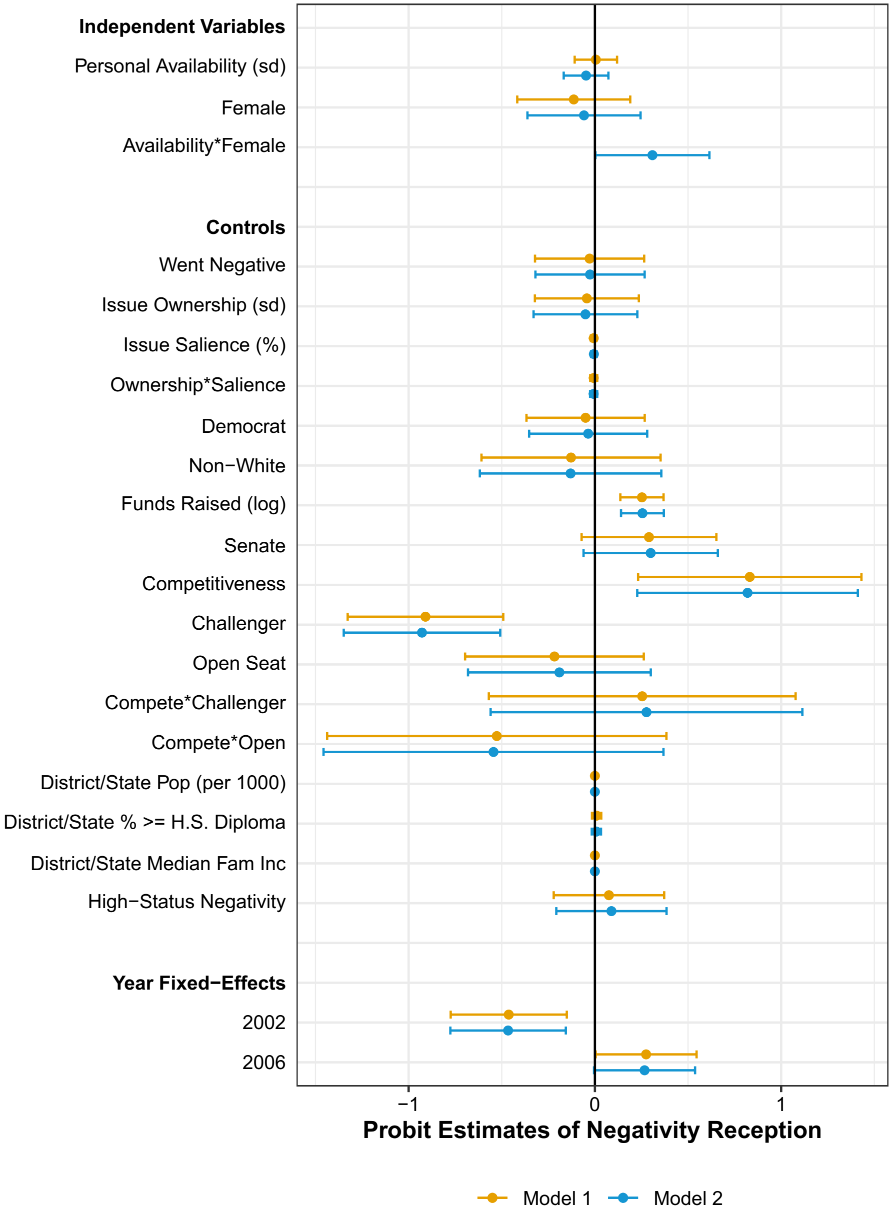

Fig. 2 Probit estimates of negativity reception, study #2. *Note* Constants = − 3.740** and − 3.679**, respectively, where **p < 0.01 (two-tailed tests). Points are probit coefficients; error bars are 95% confidence intervals. *N* = 690 for both models. Reference year is 2004. Confidence intervals derived from standard errors clustered within 604 candidates

Table 2 Fit statistics for probit models

	Model 1	Model 2
-2(*LL*)	690.363	685.957
McFadden's Pseudo-R^2	0.274	0.279
AIC	734.363	731.957
AIC_c	735.880	733.615
BIC	834.170	836.301
Likelihood ratio χ^2 (df)	–	4.406* (1)

The likelihood ratio test compares model 1 to model 2, with the former nested within the latter

*$p < 0.05$ (two-tailed test)

Robustness Check of Temporal Stability

Up to this point, the analytical assumption has been that the relationships between personalization, gender, and negativity reception do not vary across time. Since a statistically significant relationship was found in model 2, one final question might then be: to what extent is this relationship stable across electoral contexts?

To assess this question, I repeated model 2 three times: each one subsetted by election year (2002, 2004, and 2006). The results are presented as a coefficient plot in the left panel of Fig. 4 and with associated predicted probabilities per year in the right panel.[18] The personalization-gender-negativity reception association was not constant across election cycles: the personalization-gender interaction term was only statistically significant in 2002 ($\hat{\beta}_{Availability \times Female} = 0.856$; $z = 2.652$).

Discussion and Conclusion

Summary of the Argument

In this paper, I proposed that, when running for political office, a candidate's use of personal information may be linked to increases in their propensity to be the recipient of negative campaigning by their opponent. I suggested that personal information would exhibit such an association net of distinctly political information about the candidate and other known structural and contextual factors associated with negative campaigning (hypothesis #1). I grounded this proposition with insights on availability heuristics and category-based impression formation to posit that a campaign opponent may use the availability of a candidate's presentation of personal information—e.g., information on their hometowns, family, previous non-political work experience, and so on—to promote an impression of the candidate as unfit to represent their constituency. I further suggested that candidate gender might mediate this association—where female candidates are more likely to receive campaign

[18] Table versions of the models are available in Table 6 of Appendix 3.

Table 3 Average marginal effects of personal availability by gender for model 2

	AME	SE
Male	− 0.019	(0.025)
Female	0.100*	(0.049)

All additional predictor variables held at their sample (N = 690) means (for continuous variables) or modes (for categorical variables). The year variable is set to 2004

$^{*}p < 0.05$ (two-tailed test)

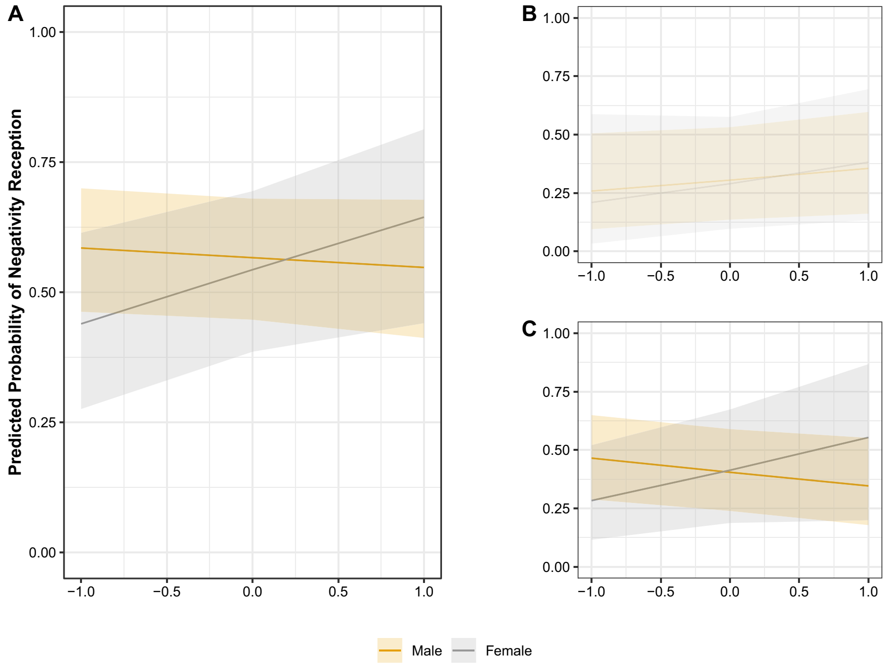

Fig. 3 Predicted probabilities of negativity reception. *Note* All additional predictor variables held at their sample ($N = 690$) means (for continuous variables) or modes (for categorical variables). The year variable is set to 2004. Bands are 95% confidence intervals. The predictions for **A** are computed from model 2 in Fig. 2. The predictions for **B** and **C** are from a version of model 2 where the sample was split by challenger and non-challenger status: **b** is derived from a sample with only challengers ($N = 287$) and panel c is derived from a sample with only incumbents ($N = 307$). For **B** and **C**, the "challenger" variable, "open seat" variable, and their associated interaction terms were removed from the equation. All other controls are held at the same sample means/modes as predictions in **A**. The transluscence of **B** signifies that that the interaction term between personal availability and candidate gender was not statistically significant at traditional alpha thresholds

negativity when making themselves more personally available than their male counterparts (hypothesis #2).

Using the case of online congressional campaigning with official website data from the 2002, 2004, and 2006 U.S. elections, I found no support for hypothesis #1. However, I found that the personalization-negativity reception relationship is moderated by candidate gender: net of political identity characteristics, sociodemographic factors, and other structural and contextual variables, female candidates who are more forthcoming with their personal information (as indicated by the presence of personal life details on their official campaign website) are also met with a higher likelihood of receiving opponent negativity. The same cannot be said for male candidates. This supports hypothesis #2. Previous literature suggests that female candidates are over-personalized in the media and subjected to questions of viability and character relative to male candidates and that female candidates are less likely to be seen as competent when they self-personalize.

This confluence of personalization dynamics may present a bind for female candidates. Women might see value in online self-personalization for reaching voters. However, just as media outlets are more likely to personalize female candidates and focus on their viability, which can lead to lower public opinion, campaign opponents may subject female candidates to negative oppositional framing on the basis of that personalization.

Importantly, though, these associations may be conditional on electoral context. A robustness check conditioning the personalization-gender interaction effect on election year revealed that the association is only statistically significant for the 2002 cycle. What it is about the 2002 congressional elections that may explain this association necessitates future research.

Presentations of Self in American Politics

Personalization and Negative Campaigning

This analysis has important implications for studying political campaigns, namely for understanding the role of candidate presentations of self. Social interaction is largely governed by (not usually conscious) efforts at "impression management"—i.e., social actors project a public self they hope will be welcomed as authentic by an audience (Goffman et al., 1959). Unsurprisingly, efforts at impression management in politics can take on a more deliberate, strategic quality. Politicians work hard to cultivate particular "front stage" public identities (Sigelman, 2001), and U.S. politicians have a particular propensity to use personal information to craft their public self on the web (Stanyer, 2008). There is a general "personalization" trend in political communication (Stanyer, 2013; van Zoonen, 2005). Politicians increasingly find themselves in the interstitial space between politics and entertainment—there is a "celebrity dimension of the contemporary politician" (van Zoonen, 2005, p. 72).

As this paper shows, however, there might be a double-edged sword when it comes to "going personal" on the campaign trail—but perhaps only for women. As an example of what this association might look like "on the ground" (in the gubernatorial context), consider the case of Democratic Texas candidate Wendy Davis. In January 2014, during primary season, *The Dallas Morning News* published a piece on Wendy Davis—then a Texas senator running for the Democratic ticket in the state gubernatorial election—citing issues in her personal narrative.[19] On the

[19] Special thanks to the anonymous reviewer who suggested this example.

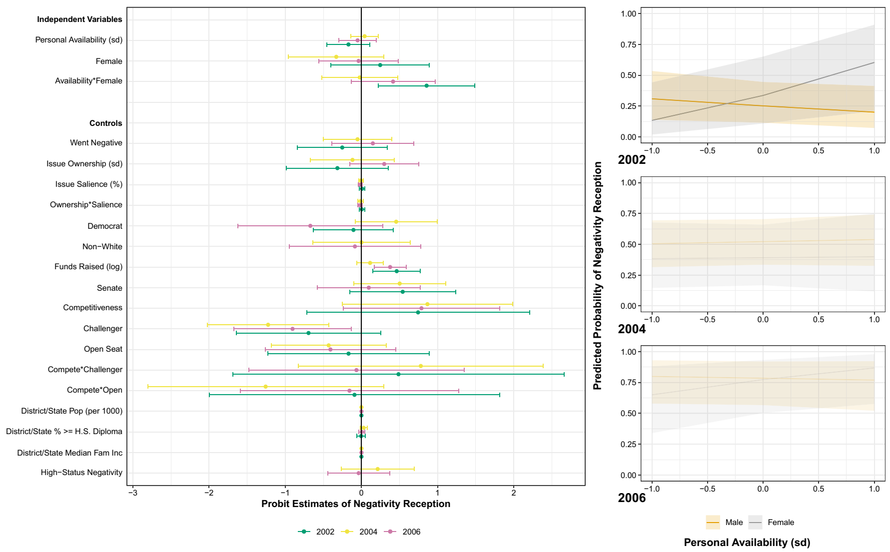

Fig. 4 Probit estimates of negativity reception (left panel) and predicted probabilities (right panel), by election year. *Note* Constants = − 6.812* for 2002, − 3.227 for 2004, and − 4.444* for 2006, where $*p < 0.05$ (two-tailed tests). Points are probit coefficients; error bars are 95% confidence intervals. N = 161, 243, and 286 for 2002, 2004, and 2006, respectively. Confidence intervals derived from cluster-robust standard errors. Non-white status and high-status negativity variables were dropped from the 2002 sample due to those cases perfectly predicted the 0 category on the dependent variable. All other controls are held at the same sample means/modes as predictions in **A** of Fig. 3. The translucence of the 2004 and 2006 panels signifies that that the interaction term between personal availability and candidate gender was not statistically significant at traditional alpha thresholds. Predicted probability parameters are the same as in Fig. 3

campaign trail in late 2013, Davis emphasized in a campaign video that, at 19 years-old, she lived in a mobile home while raising her young daughter (Davis, 2013). In the news piece, columnist Wayne Slater (2014) argued that while Davis' narrative as a "divorced teenage mother living in a trailer who earned her way to Harvard and political achievement" was factually correct, "some facts . . . [had] been blurred." For instance, Slater noted that Davis "lived only a few months in the family mobile home while separated from her husband before moving into an apartment with her daughter" (2014). GOP contender, Greg Abbott, pounced on the supposed "inconsistencies," with Abbott's communications director stating:

> Sen. Wendy Davis systematically, intentionally and repeatedly deceived Texans for years about her background, yet she expects voters to indulge her fanciful narrative . . . If voters can't trust what Sen. Davis says, how can they trust her to lead? (Camia, 2014)

Davis' personal narrative—while a potentially powerful tool for identifying with her constituents—went a long way in Abbott's framing of her as inauthentic and untrustworthy. More work is needed that bridges across the negative campaigning, personalization, and gender literatures in political campaigning studies.

Particularly, scholars should focus attention on the relational dimensions of candidates' impression management processes—how they use their personal information to craft their public self, how their opponents use that same information to assemble a version of the candidate that is their own worst foil, and how these processes unfold differently according to the gendered makeup of the campaign in question. Future research could also consider how other political actors' (e.g., donors, campaigners, activists) communication strategies might impact a candidates' likelihood of receiving opponent negativity, noting how the effects of these strategies might also be conditional on candidate gender.

Personalization as Risk-Taking

This study raises interesting questions about personalization as an electoral risk-taking strategy. Previous research suggests that congressional challengers are more likely to use "risky" campaign strategies, such as going negative, relying on technological interactivity on campaign websites, and going personal (Druckman et al., 2009, pp. 344–345). Indeed, an independent samples *t*-test using these website data suggests that challengers tend to personalize more than incumbents[20] ($t = 9.866$; $p < 0.001$, right-tailed). This difference points toward personalization as more a part of challengers' risk-taking repertoires than an incumbent strategy.

This study, however, adds an important consideration to the relationship between challenger status and risk-taking: Does the moderating effect of candidate gender on the personalization-negativity reception association vary between challenger and incumbent candidates? In other words, though incumbents are less likely to personalize, do female incumbents who *do* personalize face more risk of receiving negativity from their opponent?

I re-ran model 2 above separately for challengers ($N = 287$) and incumbents ($N = 307$) as a tentative exploration into this question. The results are displayed in the two smaller panels of Fig. 3 (and in table form with Table 5 in Appendix 2). Panel b is the challenger sample; panel c is the incumbent sample. The personalization-gender interaction term for the challenger sample was not statistically significant (thus the translucent lines and error ribbons), suggesting that the personalization-negativity reception association does not vary by candidate gender when the candidate is a challenger (and, therefore, their opponent is an incumbent). Indeed, the personalization term itself is not a statistically significant predictor when the candidate receiving negativity is a challenger—pointing to the fact the incumbents are, at baseline, simply less likely to go negative.

The same cannot be said for incumbents receiving negativity. While the personalization term by itself is not a statistically significant predictor of negativity reception among incumbents, this association does vary significantly by candidate gender (as shown in panel C). Just like in the full sample (panel A), female incumbents who personalize are also more likely to receive negativity relative to male incumbents. As such, while incumbents may be less inclined to personalize, the penalty for

[20] An incumbent was defined as a candidate who was neither a challenger nor an open-seat candidate.

doing so may be stronger for female incumbents than their male counterparts (to the extent that there is a causal arrow going directly from personalization to negativity reception).

Reciprocal Causation

The preceding sentence ends with a conditional statement about causation. This is an important point to consider as the paper concludes.

Throughout this paper, I have tried to use the language of "association" to articulate the relationship between personal availability and negativity reception. Nonetheless, the theoretical model outlined above posits a causal effect of personal availability on negativity reception during the same campaign cycle (conditional on gender). The issue, however, is that reciprocal causation between these two variables is a distinct possibility: e.g., a candidate may respond to negativity from their opponent by adding more personal information to their web presence. Instrumental variables regression models provide an ideal framework for isolating and estimating a causal effect in repeated cross-sectional samples such as these (Morgan & Winship, 2014, pp. 291–324; Muller et al., 2014). However, a theoretically-robust instrument that was simultaneously correlated with the potentially endogenous predictor (personal availability) and not correlated with the outcome model error term—and thereby satisfying the criteria of relevance and exogeneity (Stock & Watson, 2007, p. 333)—could not be found in the dataset at hand. The longitudinal nature of the data could also not be fully leveraged to estimate a causal effect: the data are unbalanced within-candidates/across election years, meaning that the sample size is too small relative to the number of estimated parameters, so the estimates derived from cross-lagged models become unreliable across even modest changes in model and covariate specification. Further, since it is difficult to assess the time frame through which personalization may causally affect negativity reception, a model would ideally include both cross-lagged *and* synchronous effects (Finkel, 1995). The lack of a quality instrument and unbalanced three-wave panel data preclude that possibility.

Future studies should therefore make specific efforts to estimate the causal effect (or lack thereof) of personalization on negativity reception, and also condition this effect on candidate gender. This will provide more explicit results for assessing the quality of the theoretical models put forth here. Using non-website data to estimate these effects will also go a long way toward understanding if these effects only hold up in online campaigning—or, like other dynamics of online campaigning (Druckman et al., 2009, 2010b; Schweitzer, 2005, 2011), if these effects in the online sphere simply reflect more the dynamics of traditional campaigning.

Appendix 1: Regression Tables for Models #1 and #2

See Table 4.

Table 4 Probit Estimates of Negativity Reception, Models #1 and #2

DV: received negativity	Model 1	Model 2
Independent variables		
Personal Availability (sd)	0.005	− 0.047
	(0.058)	(0.061)
Female	− 0.113	− 0.059
	(0.155)	(0.155)
Availability×Female	–	0.309*
		(0.156)
Controls		
Went Negative	− 0.028	− 0.026
	(0.150)	(0.150)
Issue Ownership (sd)	− 0.043	− 0.051
	(0.142)	(0.142)
Issue Salience (%)	− 0.006	− 0.005
	(0.008)	(0.008)
Ownership × Salience	− 0.006	− 0.007
	(0.010)	(0.010)
Democrat	− 0.050	− 0.036
	(0.162)	(0.162)
Non-White	− 0.128	− 0.131
	(0.245)	(0.249)
Funds Raised (log)	0.253***	0.255***
	(0.059)	(0.059)
Senate	0.290	0.299
	(0.185)	(0.184)
Competitiveness	0.831**	0.819**
	(0.306)	(0.302)
Challenger	− 0.910***	− 0.928**
	(0.213)	(0.214)
Open Seat	− 0.217	− 0.191
	(0.245)	(0.250)
Compete×Challenger	0.254	0.277
	(0.420)	(0.427)
Compete×Open Seat	− 0.527	− 0.544
	(0.465)	(0.466)
District/State Pop (per 1000)	− 0.000	0.000
	(0.000)	(0.000)
District/State % ≥ H.S. Diploma	0.009	0.008
	(0.013)	(0.013)
District/State Median Fam Inc	− 0.000	0.000
	(0.000)	(0.000)
High-Status Negative	0.075	0.089
	(0.151)	(0.151)
Year Fixed-Effects		

Table 4 (continued)

DV: received negativity	Model 1	Model 2
2002	− 0.462**	− 0.466**
	(0.159)	(0.158)
2006	0.275*	0.267
	(0.138)	(0.138)
Constant	− 3.740**	− 3.679**
	(1.212)	(1.207)
N	690	690
-2(*LL*)	690.363	685.957
McFadden's Pseudo-R^2	0.274	0.279
AIC	734.363	731.957
AIC_c	735.880	733.615
BIC	834.170	836.301
Likelihood Ratio χ^2 (df)	–	4.406* (1)

Standard errors clustered within 604 candidates

***$p < 0.001$,

** $p < 0.01$

*$p < 0.05$ (two-tailed tests)

Appendix 2: Challenger-Incumbent Sub-Sample Analyses

See Table 5.

Table 5 Probit Estimates of Negativity Reception, Study #2, Separate Challenger-Incumbent Sub-Samples

DV: Received negativity	Challenger	Incumbent
Independent variables		
Personal Availability (sd)	0.139	− 0.154
	(0.128)	(0.085)
Female	− 0.044	0.023
	(0.275)	(0.274)
Availability×Female	0.115	0.507*
	(0.348)	(0.234)
Controls		
Went Negative	− 0.007	0.275
	(0.257)	(0.276)
Issue Ownership (sd)	0.133	− .345
	(0.229)	(0.237)
Issue Salience (%)	− 0.014	0.014
	(0.012)	(0.011)
Ownership×Salience	− 0.005	0.001
	(0.014)	(0.014)
Democrat	− 0.363	0.292
	(0.308)	(0.266)
Non-White	− 0.214	0.043
	(0.400)	(0.447)
Funds Raised (log)	0.298***	0.369*
	(0.070)	(0.158)
Senate	0.107	0.352
	(0.282)	(0.334)
Competitiveness	0.944**	0.510
	(0.328)	(0.377)
District/State Pop (per 1000)	0.000	0.000*
	(0.000)	(0.000)
District/State % ≥ H.S. Diploma	− 0.001	0.016
	(0.022)	(0.020)
District/State Median Fam Inc	0.000	0.000
	(0.000)	(0.000)
High-Status Negative	0.038	0.063
	(0.256)	(0.243)
Year Fixed-Effects		
2004	0.488	0.500*
	(0.288)	(0.156)
2006	0.678*	0.863***
	(0.314)	(0.259)
Constant	− 4.083*	− 6.959**
	(1.707)	(2.449)
N	287	306
− 2(*LL*)	217.504	326.835

Table 5 (continued)

DV: Received negativity	Challenger	Incumbent
McFadden's Pseudo-R^2	0.313	0.189

Standard errors clustered within 279 challengers and 252 incumbents

***$p < 0.001$

**$p < 0.01$

* $p < 0.05$ (two-tailed tests)

Appendix 3: Separate Year Analyses

See Table 6.

Table 6 Probit Estimates of Negativity Reception, by Election Year

DV: Received negativity	2002	2004	2006
Independent Variables			
Personal Availability (sd)	− 0.170	0.042	− 0.050
	(0.144)	(0.092)	(0.125)
Female	0.246	− 0.330	− 0.037
	(0.330)	(0.320)	(0.265)
Availability×Female	0.856**	− 0.022	0.415
	(0.323)	(0.254)	(0.281)
Controls			
Went Negative	− 0.252	− 0.051	0.150
	(0.301)	(0.230)	(0.275)
Issue Ownership (sd)	− 0.316	− 0.117	0.299
	(0.342)	(0.281)	(0.232)
Issue Salience (%)	0.010	− 0.005	− 0.014
	(0.018)	(0.014)	(0.012)
Ownership×Salience	0.006	− 0.013	− 0.018
	(0.019)	(0.019)	(0.014)
Democrat	− 0.105	0.456	− 0.671
	(0.267)	(0.275)	(0.485)
Non-White	–	0.000	− 0.086
		(0.327)	(0.440)
Funds Raised (log)	0.463**	0.114	0.377***
	(0.159)	(0.088)	(0.107)
Senate	0.542	0.502	0.096
	(0.355)	(0.309)	(0.344)
Competitiveness	0.744	0.866	0.788
	(0.746)	(0.570)	(0.524)
Challenger	− 0.695	− 1.225**	− 0.904*
	(0.483)	(0.405)	(0.392)
Open Seat	− 0.169	− 0.430	− 0.407
	(0.540)	(0.385)	(0.438)

Table 6 (continued)

DV: Received negativity	2002	2004	2006
Compete×Challenger	0.486	0.779	− 0.065
	(1.111)	(0.820)	(0.720)
Compete×Open Seat	− 0.091	− 1.257	− 0.157
	(0.973)	(0.790)	(0.732)
District/State Pop (per 1000)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
District/State % ≥ H.S. Diploma	− 0.004	0.029	0.006
	(0.028)	(0.023)	(0.020)
District/State Median Fam Inc	0.000	0.000	0.000
	(0.000)	(0.000)	0.000
High-Status Negative	–	0.213	− 0.036
		(0.244)	(0.208)
Constant	− 6.812*	− 3.227	− 4.444*
	(2.974)	(1.909)	(2.175)
N	161	243	286
− 2(*LL*)	155.441	250.249	245.265
McFadden's Pseudo-R^2	0.261	0.243	0.379
AIC	193.441	292.248	287.265
AIC_c	198.831	296.429	290.765
BIC	251.988	365.603	364.041

Robust standard errors in parentheses. The Non-White dummy variable was dropped from the 2002 model because there were no non-white candidates in the model after listwise deletion on the other covariates. The High-Status Negative variable was also dropped from the 2002 analysis because the individual dummy variable that constitute that variable were not recorded for the 2002 election cycle

***$p < 0.001$

**$p < 0.01$

* $p < 0.05$ (two-tailed tests)

Appendix 4: On the Choice of the Dependent Variable

The dependent variable used here conflates receiving personal negativity with receiving issue-based negativity. The dataset also includes dummy variables for whether or not the candidate *themselves went* negative at the level of the personal and/or at the level of issues. New variables can therefore easily be constructed that "match" each candidate with their opponent and report whether or not the candidate *received* personal negativity explicitly (net of issue-based negativity).

The issue, however, is this: these dummy variables only exist for the 2004 and 2006 cycles—the two election years where the relationship of interest (i.e., the relationship between negativity reception and the personalization-gender interaction) is not statistically significant (see the "Robustness Check of Temporal Stability" section of the paper). As such, for the election cycle where the association likely can't be attributed solely to random chance, there is no way to disentangle the outcome variable into personal vs. issue-based sources of opponent negativity.

That said, I still created a new version of the outcome variable for the 2004 and 2006 elections—where 0 = *did not receive* personal negativity from the opponent and 1 = *did receive* personal negativity from the opponent. While the relationship is not statistically significant, the coefficients are signed in the expected directions for 2006 ($\hat{\beta}_{Availability} = 0.070$; $\hat{\beta}_{Female-Male} = 0.013$; $\hat{\beta}_{Availability \times Female} = 0.205$).

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