Supplementary Information (SI)

Women and Men Politicians' Response to War: Evidence from Ukraine

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Contents

S1 Case Selection & Dataset

As we explain in the main text, our empirical strategy relies on observing the behavior of Ukrainian politicians on social media before and after the 2022 Russian invasion of Ukraine. For our purposes, this case offers design advantages and is generalizable as we discuss below. In S1.2, we then describe the dataset on Ukrainian politicians' Facebook pages.

S1.1 Case Selection and Context

Regarding the design advantages, the availability of social media data for a large share of politicians allows us to observe politicians' behavior in real time before and after the start of the conflict. Furthermore, the timing and severity of this invasion came as a surprise to the public and experts alike. As Michael Carpenter, U.S. ambassador to the Organization for Security and Cooperation in Europe, articulated, "There is a distinction between the plausibility of something and the shocking nature of something that is so epic in its proportions...it did seem plausible, but it was also deeply, deeply shocking" (Banco et al. 2023). Despite intelligence reports of Russia bolstering forces along the border, Defense Minister Oleksii Reznikov told parliamentarians that there were "no grounds to believe" Russia would invade (Karmanau 2022). President Zelenskyy repeated the sentiment, asking citizens to "calm down" and assuring that the threat from Russia had not increased (Quinn 2022). The surprising timing of the invasion provides us with a quasi-experimental setting where it is reasonable to assume that politicians' behavior would not have changed were it not for the invasion. Employing interrupted time series (ITS) analyses with these data allows us to causally estimate the effect of the invasion on politicians' behavior (McDowall et al. 2019).

In terms of generalizability, responses in the most recent World Values Survey (2017-2022) indicate that gender norms in Ukraine are on par with the global average, although Ukrainians are less gender egalitarian in questions pertaining to women politicians and business leaders. Further enhancing the generalizability is the fact that the war between Russia and Ukraine offers a difficult test of our argument. While the invasion was unexpected, Russia and Ukraine have been in conflict since 2014.[1] It is therefore possible that politicians would have assumed gender-stereotypical behaviors for years prior, making any changes from before to after the invasion more difficult to uncover. If we do find an effect, however, our argument is likely to be generalizable.

Women have been active and visible in Ukrainian resistance efforts since conflict began in 2014 (see Phillips and Martsenyuk 2023). However, this does not necessarily mean that gendered expectations might not apply in this context. In fact, O'Sullivan (2019) shows how this conflict has encouraged anti-feminist and stereotypically gendered behavior among public figures and "mainstream Ukrainians" (see also Harrison 2022). In the end, the extent to which gendered expectations do not apply, it will be harder for us to find the hypothesized relationship, contributing to this conflict being a hard test case for our purposes.

[1] Although Ukraine and Russia have been at war since 2014, the invasion dramatically increased the intensity of conflict as if a new war had begun. According to the Armed Conflict Location & Event Data Project (ACLED), the month before the invasion saw 152 battles and 271 instances of remote violence, whereas these increased to 662 and 1344 respectively the month following invasion.

S1.2 Data on Ukrainian Politicians' Facebook Pages

We constructed our dataset on Ukrainian politicians' Facebook pages through the following steps. First, we obtained the lists of politicians who were in power during the period around the invasion from the respective websites of the different institutions (i.e., the parliament, the cabinet of ministers, the oblast governments, as well as the website of the Central Electoral Commission of Ukraine) and general Google search results. Second, we hired native Ukrainian research assistants through an online platform called Upwork to cross-check our list and identify each politician's public Facebook pages. We only retain Facebook urls that were confirmed by at least two independent RAs. Lastly, we used CrowdTangle API to collect every Facebook post from politicians' Facebook pages that were available at the time of collection. We repeated the API calls from the end of April 2022 to June 2022 to make sure we do not miss any posts. Our final dataset includes 136,455 posts written by 469 Ukrainian politicians: 388 men and 81 women.

The total number of politicians who served during this period was 983, including 446 members of parliament, 461 mayors, 23 cabinet members, one president, 26 oblast leaders and 26 chairs of regional councils. Of all politicians, we identified 154 women and 825 men. This means that we were able to identify Facebook accounts for approximately 48% of all politicians in Ukraine (approximately 53% of all women and 47% of all men).

Among the 469 politicians who used Facebook around the invasion, there are 290 members of parliament, 127 mayors, 15 cabinet members including the president, 18 oblast (i.e., regional) governors, and 19 chairs of oblast councils. The largest share of women appears among the chairs of regional councils (32 percent), and the smallest among mayors (5 percent). In terms of partisanship, there are 35 parties represented by the politicians in our data. The top three parties represented are Servant of the People (42%), European Solidarity (6%), and Batkivshchyna ("Fatherland," 5%). A sizeable portion are independents (12%). The majority of members of parliament identify with Servant of the People (62%), while mayors tend to represent smaller local parties.

S2 Topic Modeling and Labels

In order to measure the topics politicians discuss in their posts, we apply unsupervised topic modeling, Top2Vec, and examine the substantive content of posts (Angelov 2020). This model is a type of natural language processing (NLP) model that transforms the text into a vector representation and assigns similar texts into clusters based on their distance to each other in the vector space. It first generates joint embedding vectors for documents and words to represent them in a multi-dimensional vector space while retaining the order of the sequence of words. Then, it performs dimensionality reduction and identifies dense areas of the embedding vectors as well as the topic words that attracted the documents together. The topic vector is calculated as the center of the cluster. After the topic vectors are calculated, we assign substantive labels to topics based on our understanding of both the topic words and documents that are proximate to the topic vector in the vector space.

After running Top2Vec with the Facebook posts, we find 907 clusters of posts that share similar meanings. Two of the three authors then manually inspected each topic individually and assigned a topic label to each. The intercoder reliability was 71% over the 907 topics. The coders addressed each disagreement and resolved them by reaching a unanimous decision. Table S2.1 describes the criteria (i.e., coding rules) for each of the topic labels as well as some of the keywords from topic clusters that were assigned to each label. Note that the list of keywords is illustrative, not comprehensive. The percentage of Facebook posts assigned to each label is indicated in parentheses.

Table S2.1: **Topic Labels**

Label	Description	Keywords
Social aid (18.1%)	Provision of government services in/out of wartime; evacuation and resettlement during wartime; calling for volunteers/donations within Ukraine; discussion and/or legislation about infrastructural support system	evacuation, corridors, volunteers, development, renovation, benefits, vouchers, autostradna with other traffic terms, diya/diia (government app), convoys, IDPs
Morale boost (13.2%)	Commemorating historical events and loss in wartime; boosting morale in wartime; highlighting heroism and bravery of Ukrainians; celebrating Ukrainian traditions and domestic holidays	brave, heroes, warship stamp, commemorate, Holodomor, indomitable, UPA, OUN, tradition, folk, Plast, Sumschina
Security (20.9%)	Providing information on emergencies such as air raids; updating news from the battlefields; posts about nuclear plants; food/energy/public health security; legislation about security	checkpoint, roadblock, siren, alarm, alert, COVID, vaccines, death, capture, Molotov cocktails, fire, ammonia
Foreign affairs (12.4%)	Diplomatic events; global sanctions against Russia; discussing Russia's interaction with other foreign bodies; currency exchange rates; discussing war crimes; discussing NATO/EU membership; discussing foreign donations and aid; international media attention on Ukraine	country names, dollar, EU, NATO, Nuremberg, Tribunal, CNN, BBC, diplomatic, names of leaders
Legislation (5.3%)	Discussing policymaking in parliament; promoting new legislation (except for legislation on social aid and security); discussing tax, tariffs, and reforms	bill, tariff, tax, reform, regulate, legislation, Verkhovna Rada
Religion (4.6%)	Discussing Christianity in Ukraine; celebrating religious holidays	Christmas, resurrection, Easter, genesis, hetman, beatitude, annunciation, Pechersk Lavra
Addressing Russia (3.5%)	Verbal appeals to Russia; calling for action from Russians; emotionally charged discussions of Russia; calling names	sons, wives, mothers, forgive, dearest, grief, bastards, kill, rashists, Putin, dictator, fascists, Nazi, orcs
Others (21.9%)	Discussing sports and entertainment; personal briefings; other noise	tv, espresso, Youtube, Poroshenko, court, judicial, corruption, birthday

S3 Additional Analyses for H1: Men Engage More than Women

S3.1 Controlling for Political Office

In this section we perform an additional analysis that controls for different political offices held by the politicians in our data. These include the following (with the proportion of women in each position stated in the parentheses) mayors (6 out of 127), MPs (65 out of 290), cabinet members (3 out of 15), oblast governors (1 out of 18), and chairs of oblast councils (6 out of 19). This analysis accounts for the possibility that different types of political offices may create different incentives for public engagement and drive the gender gap pattern we see in the post-invasion period.

Table S3.1 presents the result. The gendered effect of the invasion on politicians' public engagement remains significant after controlling for different types of political offices.

Table S3.1: **Effect of War on Politicians' Engagement with Office Controls**

	Posts per politician
Invasion	2.53^{***}
	(0.16)
Woman	0.33
	(0.36)
Invasion × Woman	-0.35^{***}
	(0.09)
Time	0.00^{***}
	(0.00)
Time since invasion	-0.03^{***}
	(0.00)
Cabinet	0.38
	(0.59)
Governor	2.49^{***}
	(0.96)
Mayor	0.27
	(0.38)
MP	0.25
	(0.43)
Intercept	0.19
	(0.35)
$\hat{\sigma}_{\text{id}}$	2.23
$N_{Observations}$	99897
$N_{Politicians}$	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variable, *Posts per politician*, indicates the number of Facebook posts by each politician-day unit. The model also includes random intercepts by politician, and $\hat{\sigma}_{\text{id}}$ indicates the estimated standard deviation of the random effects. The baseline category for political office is *Chairs of regional council*. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S3.2 Controlling for Regional Variations

In this section, we perform an additional analysis that controls for politicians' regions in our test of H1. This allows accounting for potential spatial variation that may affect our findings. For example, politicians with constituencies closer to areas affected by violence may behave differently than those whose constituencies experienced less or no violence. It is also possible that politicians' access to internet varied geographically, as critical infrastructure was damaged in some locations during the invasion.

Since we do not have the precise location of politicians, we use the oblast of the politician's constituency as a proxy for location of politicians. We use 25 regions that include the 24 oblasts in Ukraine and the capital city of Kyiv. We have oblast-level indicators for 328 politicians that include mayors, governors, chairs of regional council, and members of parliament that were elected from single-member constituencies (50% of all parliamentary seats). For politicians with national constituencies such as cabinet members and 50% of MPs, we code their region as "None."

Table S3.2 shows that our substantive findings are robust to the inclusion of region controls. While these controls may not perfectly proxy the accurate location of politicians at the time of the invasion, this analysis shows that politicians representing constituencies more proximate to violence are not driving the results.

Table S3.2: **Effect of War on Politicians' Engagement with Region Controls**

	Posts per politician
Invasion	2.53^{***}
	(0.16)
Woman	0.34
	(0.28)
Invasion × Woman	-0.35^{***}
	(0.09)
Time	0.00^{***}
	(0.00)
Time since invasion	-0.03^{***}
	(0.00)
Intercept	0.51^{**}
	(0.22)
Region controls	✓
$\hat{\sigma}_{\text{id}}$	2.22
$N_{Observations}$	99897
$N_{Politicians}$	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variable, *Posts per politician*, indicates the number of Facebook posts by each politician-day unit. The model also includes random intercepts by politician, and $\hat{\sigma}_{\text{id}}$ indicates the estimated standard deviation of the random effects. The baseline category for region is *None*. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S3.3 Committee Assignments and Posting Behavior

As we note in the main text, we expect our argument to hold for women and men politicians in general. That said, one might argue that legislative committee assignments can affect the relationship between politicians' gender and their communication behavior on Facebook. More specifically, gender stereotypes can affect the committee assignments for women politicians, which in turn would affect the way they communicate with the public, especially when a sudden threat, such as invasion, highlights gender stereotypes.

We relied on the Verkhovna Rada website to identify 26 committees and their membership. Note that only MPs in our sample can have committee assignments and not all MPs have been assigned to a committee.[2] Table S3.3 presents the distribution of women politicians by committee. The list is sorted by proportion of women politicians in a descending order. Note that the category "None" includes both MPs without committee assignments and non-MPs.

Table S3.3: **Distribution of Committee Assignment by Gender**

Committee	**N (Politicians)**	**N (Women)**	**Proportion**
Education, Science and Innovations	8	4	0.50
Ukraine's Integration into the European Union	7	3	0.43
Rules of Procedure, Parliamentary Ethics	5	2	0.40
Youth and Sports	5	2	0.40
Public Health, Medical Assistance and Medical Insurance	13	5	0.38
Anti-Corruption Policy	8	3	0.38
Humanitarian and Information Policy	16	6	0.38
Social Policy and Protection of Veterans' Rights	6	2	0.33
Finance, Taxation and Customs Policy	25	7	0.28
Digital Transformation	4	1	0.25
State Power, Local Self-Government, Urban Planning	20	5	0.25
Law Enforcement Activities	13	3	0.23
Economic Development	14	3	0.21
Foreign Policy and Inter-Parliamentary Cooperation	5	1	0.20
Environmental Policy and Nature Management	11	2	0.18
Energy, Housing, Utilities Services	19	3	0.16
National Security, Defence and Intelligence	13	2	0.15
Budget	30	4	0.13
Transport and Infrastructure	17	2	0.12
Agrarian and Land Policy	19	2	0.11
None	190	19	0.10
Freedom of Speech	3	0	0.00
Human Rights, National Minorities and Interethnic Relations	8	0	0.00
Legal Policy	9	0	0.00
Ukraine Committee on Finance, Taxation and Customs Policy	1	0	0.00

Table S3.4 shows the regression result for our main analysis with committee assignments as a control variable. We find that our substantive findings are robust. Even after controlling for committee assignments, women politicians post significantly less than men following the invasion.

[2]In our data, 11 MPs (8 men, 3 women) were not assigned to any committees.

Table S3.4: **Effect of War on Politicians' Engagement with Committee Controls**

	Posts per politician
Invasion	2.53^{***}
	(0.16)
Woman	0.28
	(0.30)
Invasion $\times$ Woman	-0.35^{***}
	(0.09)
Time	0.00^{***}
	(0.00)
Time since invasion	-0.03^{***}
	(0.00)
Intercept	0.66^{***}
	(0.15)
Committee controls	✓
$\hat{\sigma}_{\mathrm{id}}$	2.28
$N_{Observations}$	99897
$N_{Politicians}$	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variable, *Posts per politician*, indicates the number of Facebook posts by each politician-day unit. The model also includes random intercepts by politician, and $\hat{\sigma}_{\mathrm{id}}$ indicates the estimated standard deviation of the random effects. The baseline category for committee assignments is *None*.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S3.4 Foreign Policy Elites and Posting Behavior

In addition to committee assignments, one might also argue that women who are foreign policy elites choose not to divert to the kinds of gender-stereotypical roles we discussed in the main text (see Caprioli 2000; Goldstein 2001; McGlen and Sarkees 1993). Outside of MPs, we could not identify any women politicians in a position that can be considered as a foreign policy elite. In terms of committee assignments for MPs, there is one woman MP in the "Foreign Policy and Inter-Parliamentary Cooperation" committee. If we consider "Ukraine's Integration into the European Union" and "National Security, Defence and Intelligence" to also be foreign policy related committees, we have six women politicians whom we can consider to be part of the foreign policy elite. Based on this classification, we constructed a binary variable *Foreign* that equals 1 if a politician is assigned to any one of the three committees mentioned above. Then, we included *Foreign* in the model as a control in order to see if our results are driven by the behavior of foreign policy elites. Table S3.5 presents the results. We find that our substantive findings remain robust.

Table S3.5: **Effect of War on Politicians' Engagement, Controlling for Foreign Policy Elite**

	Posts per politician
Invasion	2.53^{***}
	(0.16)
Woman	0.25
	(0.31)
Invasion × Woman	-0.35^{***}
	(0.09)
Foreign	-0.37
	(0.32)
Time	0.00^{***}
	(0.00)
Time since invasion	-0.03^{***}
	(0.00)
Intercept	0.56^{**}
	(0.22)
$\hat{\sigma}_{\text{id}}$	2.26
$N_{Observations}$	99897
$N_{Politicians}$	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variable, *Posts per politician*, indicates the number of Facebook posts by each politician-day unit. The model also includes random intercepts by politician, and $\hat{\sigma}_{\text{id}}$ indicates the estimated standard deviation of the random effects. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S4 Additional Analyses for H2: Role-Congruent Tone and Issues

S4.1 Sentiment Analysis with Politician-Day Unit

The unit of analysis in the main text's sentiment analysis is the Facebook post. We examine the robustness of our results by using an alternative unit of analysis: the politician-day. The results are presented in Table S4.1 and confirm the substantive finding of the main analysis by showing that invasion makes women politicians more positive than men politicians: the interaction between the invasion and politician gender is positive in the case of all four dictionaries and statistically significant in three of the four dictionaries.

Table S4.1: **Effect of War on Positive Sentiment with Politician-Day Unit**

	Positive sentiment			
	SYUZHET	NRC	AFINN	BING
Invasion	-2.20^{***}	-2.93^{***}	-3.61^{***}	-1.77^{***}
	(0.07)	(0.10)	(0.13)	(0.06)
Woman	0.01	0.18	-0.51	-0.38^{*}
	(0.26)	(0.38)	(0.48)	(0.22)
Invasion × Woman	0.17^{*}	0.25^{*}	0.34	0.26^{***}
	(0.10)	(0.14)	(0.21)	(0.09)
Time	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Time since invasion	0.03^{***}	0.03^{***}	0.05^{***}	0.02^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	4.52^{***}	6.74^{***}	7.11^{***}	2.82^{***}
	(0.13)	(0.18)	(0.24)	(0.11)
$\hat{\sigma}_{\text{id}}$	1.68	2.40	3.03	1.36
$N_{Observations}$	43526	43526	43526	43526
$N_{Politicians}$	469	469	469	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variables are average sentiment scores for each politician-day unit calculated with respective dictionaries. The models also include random intercepts by politician, and $\hat{\sigma}_{\text{id}}$ indicates the estimated standard deviation of random effects. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S4.2 Changes in Topic Proportions with Binomial Logistic Regression

Note that in the analysis of topic proportions, for each politician-day unit, topic proportions are calculated by counting the number of posts that belong to a given topic divided by the total number of posts. With this operationalization, we create a proportional response variable where the values are restricted to be in $[0, 1]$. We fit a binomial logistics regression that takes the response variable as the proportion of successes and the total number of trials as weights to account for the characteristic of proportional response variables. Table S4.2 presents the results that are consistent to the findings in the main text. A model that includes random intercepts by politician failed to converge, which is why we are reporting the results of a model without random intercepts. All other modeling choices remain the same.

Table S4.2: **Effect of War on Topic Proportions (Binomial Logit)**

	Topic proportion		
	Social aid	Morale boost	Security
Invasion	0.07	-0.52^{***}	1.14^{***}
	(0.07)	(0.09)	(0.07)
Woman	-0.28^{***}	-0.12^{***}	0.11^{**}
	(0.04)	(0.04)	(0.04)
Invasion × Woman	0.19^{***}	0.29^{***}	-0.32^{***}
	(0.05)	(0.05)	(0.06)
Time	-0.00^{***}	0.00	0.00^{**}
	(0.00)	(0.00)	(0.00)
Time since invasion	0.01^{***}	0.01^{***}	-0.01^{***}
	(0.00)	(0.00)	(0.00)
Intercept	-1.12^{***}	-1.94^{***}	-2.18^{***}
	(0.04)	(0.10)	(0.06)
AIC	79977.13	67317.17	74646.47
Log Likelihood	−39982.57	−33652.59	−37317.23
$N_{Observations}$	43526	43526	43526

Note: Table entries represent the change in log odds of the outcome from a unit-change in the predictor with Newey-West adjusted standard errors in parentheses. The dependent variables are proportions of the respective topics (for each politician-day unit) noted in column headings. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S4.3 Changes in Proportions of Gender-Ambiguous Topics

In this section, we present changes in topic proportions before and after the invasion for the remaining topics. Recall that our hypothesis only applies to topics that we can confidently classify as feminine or masculine. As we explain in the main text, we rely on a sizeable literature in political science to identify issues as part of the feminine vs. masculine domain (Baekgaard and Kjaer 2012; Escobar-Lemmon and Taylor-Robinson 2009; Krook and O'Brien 2012; Paxton et al. 2020; Swers 2002), and classify the topics of *Social aid*, *Morale boost*, and *Security* as having clear gendered expectations.

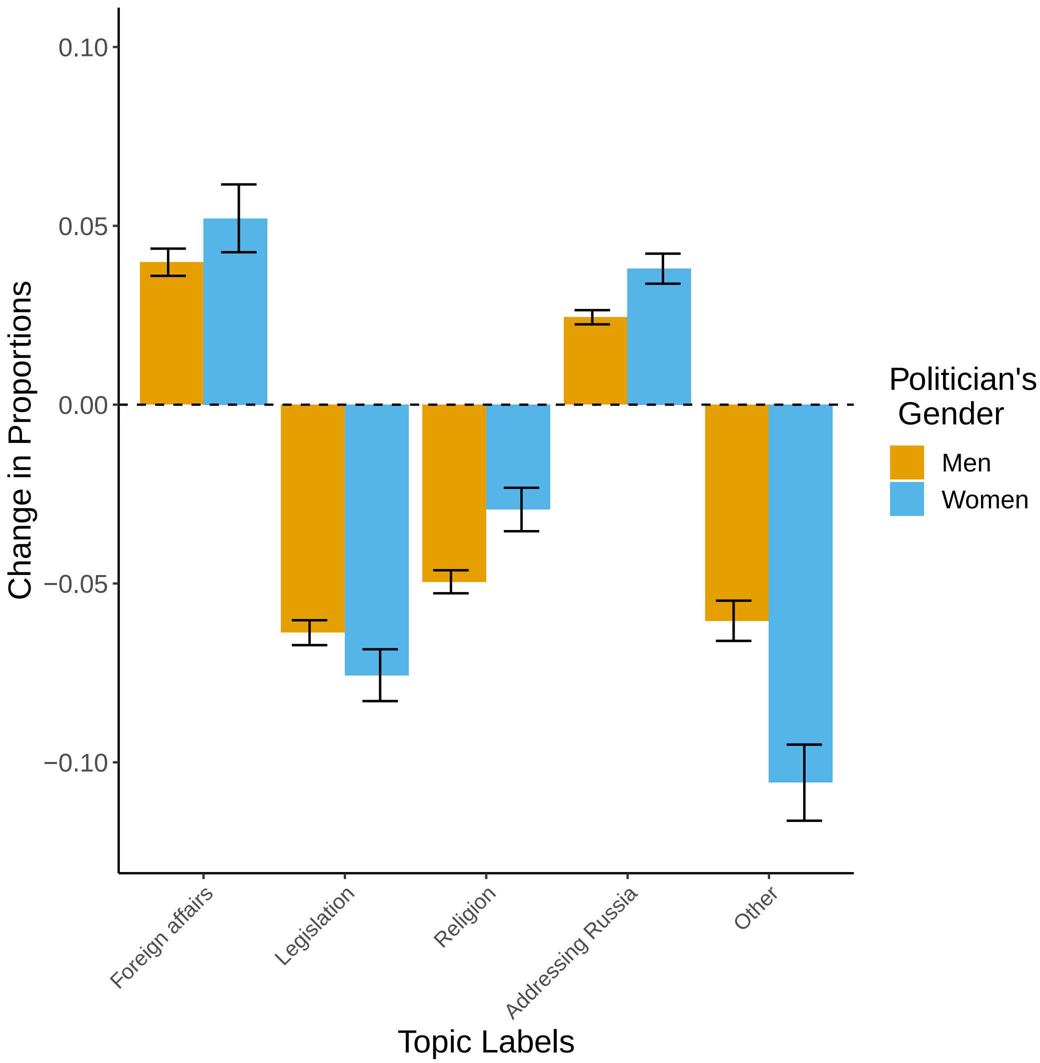
The literature does not provide a clear backing for categorizing the remaining topics as gendered. Please refer to Table S2.1 for substantive descriptions of each topic label. For example, whether *Foreign affairs*, as measured here, is feminine or masculine remains ambiguous because this topic includes elements of both aid and security, as well as gender-neutral themes such as international media attention (see Table S2.1). The classification of this topic is further complicated by the fact that, post-invasion, men between ages 18-60 were restricted from leaving the country, which meant that women had to take over at least some of the diplomatic travel (Basu 2022). Similarly, *Addressing Russia*, is a category that includes elements of both femininity (appeals) and masculinity (attacks), leaving it gender-ambiguous.

The categorization of the topics *Legislation*, *Religion*, and *Other* is even more ambiguous – the category descriptions do not include themes that previous literature would clearly identify with obvious gender connotations. Because of this, we were concerned that any categorization of these as feminine or masculine would be arbitrary. Furthermore, our theory only applies to women's and men's behavior on clearly feminine and masculine topics. We lack expectations for men's and women's behavior on these additional domains and cannot use them for theory testing. Even if gendered patterns emerge on any of these other topics, it does not undermine our main findings. The patterns on these residual categories may emerge for idiosyncratic reasons that call for further theorizing, which is beyond the scope of this paper.

That said, we present here the comparison of the remaining topics for the sake of completeness, and because exploring gender differences across other topics descriptively is interesting in its own right. Figure S4.1 replicates Figure 2 in the main text for the remaining topics. Figure S4.2 presents the same information in a way that facilitates within-gender comparison of changes in topic proportions pre-post invasion.

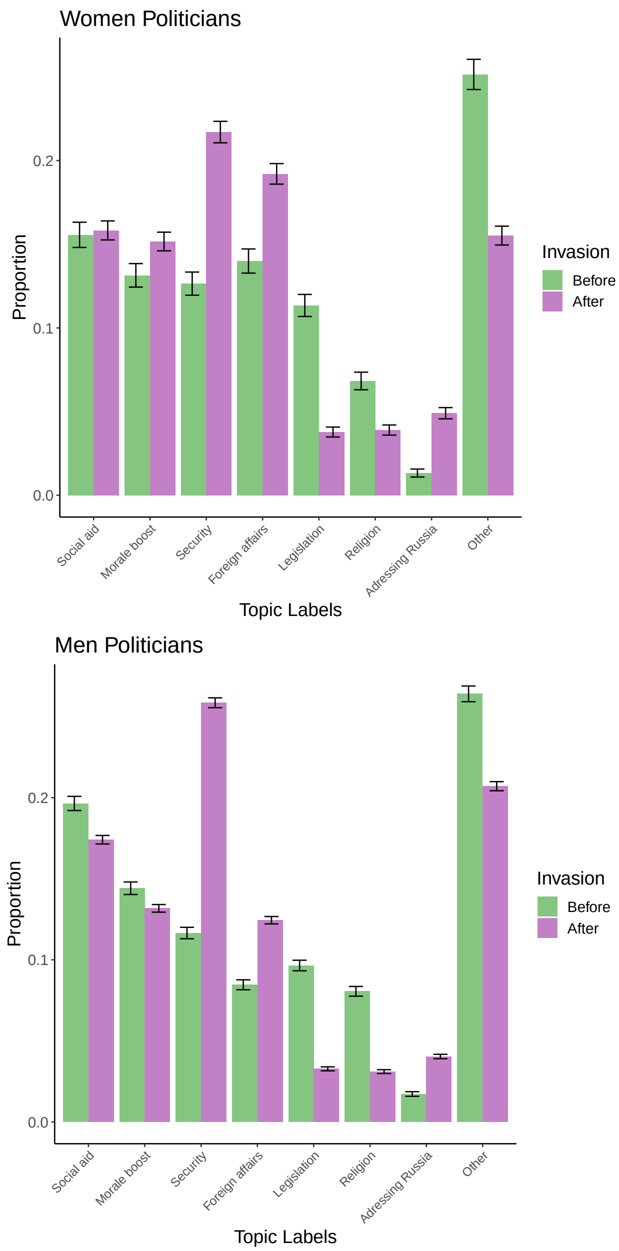
Looking at Figure S4.1, we see that whether and how the invasion affects topic proportions differently for women and men varies across the remaining topics. For example, both women and men increase their proportion of posts on *Foreign affairs*, and rate of change looks relatively similar across genders, perhaps reflecting the fact that this category is not obviously feminine or masculine in our coding. Post invasion, both women and men politicians also increase the number of posts that fall into the category *Addressing Russia*. The increase among women is somewhat larger than that among men, but not sizeably so. Somewhat greater gender differences do emerge on other topics, but without theoretical guidance, these aren't easy to interpret. We see that, on average, both men and women politicians significantly reduce their posts on the gender-ambiguous topics of *Legislation*, *Religion*, and *Other* (see also Figure S4.2, which confirms that the reduction of attention is significant for both women and men). This is understandable in the context of war, but also interesting in the context of our analysis because it suggests that politicians of both genders may be trading off the more gender ambiguous topics for the more clearly feminine or masculine ones. We also see that on the topics of *Legislation* and *Other*, the reduction among women is larger than that among men, while on *Religion*, the pattern is the opposite.

Figure S4.1: **Changes in All Topic Proportions Before and After the Invasion, by Gender**



Note: Bars represent the difference between pre-invasion and post-invasion topic proportions (Post − Pre). The lines represent the respective 95% confidence intervals.

Figure S4.2: **Pre-Post Invasion Changes in Topic Proportions for Women and Men Politicians**



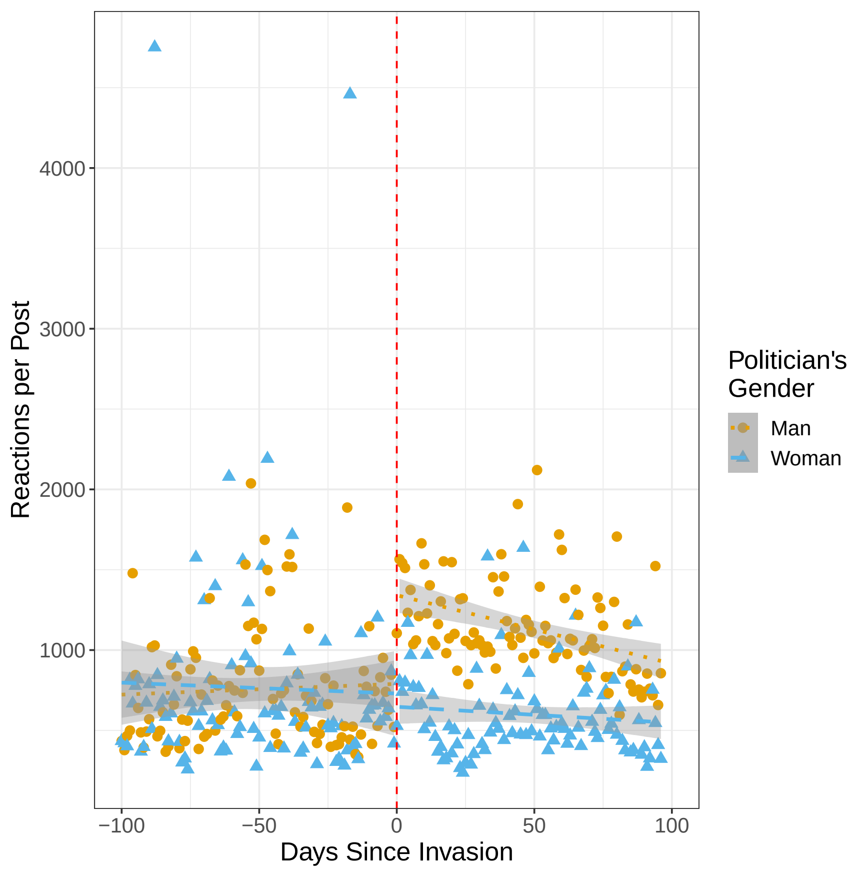
Note: The plot shows the changes in topic distributions of politicians' posts before and after the invasion. The bars represent the proportion of posts that are assigned to the corresponding topic labels. The lines represent the respective 95% confidence intervals.

S5 Additional Analyses for Extension: Citizens Prefer Men's Engagement

S5.1 Full Plot for Figure 3

This section replicates Figure 3 in the main text with all observations included. Recall that two outliers were omitted from Figure 3 for better visualization. The interpretation of the results remains the same with all observations included.

Figure S5.1: **Daily Average Reactions Per Post Before and After the Invasion**



Note: This figure represents the daily average reactions to Ukrainian politicians' Facebook posts before and after the Russian invasion of Ukraine on February 24th, 2022. The unit of data is day-gender, meaning that each blue triangle represents the average reactions received on posts by women politicians and each yellow dot those received on posts by men politicians on a given day. The vertical dotted line notes the start of the invasion. The blue and yellow lines represent predicted values and the gray areas represent the respective 95% confidence intervals.

S5.2 Reactions with Politician-Day Unit

The unit of analysis in the main text's reaction analysis is the Facebook post. We examine the robustness of our results by using an alternative unit of analysis: the politician-day. The results are presented in Table S5.1 and confirm the substantive finding of the main analysis by showing that invasion makes women politicians receive less reactions than men politicians.

Table S5.1: **Effect of War on Public Reactions with Politician-Day Unit**

	Reactions
Invasion	687.73^{***}
	(87.87)
Woman	26.67
	(255.60)
Invasion × Woman	-385.30^{***}
	(59.76)
Time	1.55^{***}
	(0.52)
Time since invasion	-7.89^{***}
	(1.34)
Intercept	340.62^{**}
	(161.25)
$\hat{\sigma}_{\text{id}}$	2668.49
$N_{Observations}$	43526
$N_{Politicians}$	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variable, *Reactions*, is the average number of reactions received by each politician-day unit. The model also includes random intercepts by politicians, and $\hat{\sigma}_{\text{id}}$ indicates the estimated standard deviation of the random effects. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S5.3 Reactions with Office and Post Type Controls

We perform additional robustness checks to account for the possibility that Facebook's algorithm may promote certain types of posts (e.g., videos) more than simple text-only posts, or posts written by more prominent politicians. To address this issue, we add control variables for politicians' positions and Facebook post types. Table S5.2 presents the results. The effect of war on reactions is consistent with the results presented in the main text.

Table S5.2: **Effect of War on Public Reactions, Controlling for Office and Post Types**

	Reactions
Invasion	785.64^{***}
	(49.59)
Woman	64.90
	(225.53)
Invasion × Woman	-480.17^{***}
	(58.83)
Time	1.53^{***}
	(0.42)
Time since invasion	-9.48^{***}
	(0.85)
Intercept	-492.29^{***}
	(108.49)
Office controls	✓
Post type controls	✓
$\hat{\sigma}_{\text{id}}$	2814.65
$N_{Observations}$	136455
$N_{Politicians}$	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variable, *Reactions*, is the number of total reactions received by each post. The model also includes random intercepts by politicians, and $\hat{\sigma}_{\text{id}}$ indicates the estimated standard deviation of the random effects. The baseline category for political offices is *Chairs of regional council*, and the baseline category for post types is *Status*. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S5.4 Different Types of Reactions

To complement the analyses in the main text, we further disaggregated voter reactions in order to examine whether the effect of the war is different depending on how the audience engages with the politician. The first column in Table S5.3 replicates the results in Table 4 of the main text with the aggregate measure of all *Reactions* as the dependent variable. The subsequent columns use the different types of reactions as dependent variables, as indicated in the column headings. In each case, the dependent variable is the average amount of a certain type of post interactions received by each post on a given day. Likes, Comments, Shares, Loves, and Angers indicate the number of Like, Comment, Share, Love, and Anger interactions received by a post, respectively. Among the seven emoji reactions (Like, Love, Care, Haha, Wow, Sad, Angry), we choose Like, Love, and Angry. Like is a reaction that is most frequently used, while Love and Angry are reactions that are most correlated with positive and negative emotions (Muraoka et al. 2021). We find that the gendered effect of war on reactions reported in the main text is consistent across different reaction types.

Table S5.3: **Effect of War on Public Reactions for Different Reactions**

	Reactions	Like	Comment	Share	Love	Angry
Invasion	771.06***	349.92***	53.29***	170.79***	51.13***	9.63***
	(49.50)	(27.72)	(9.72)	(11.22)	(5.56)	(2.60)
Woman	62.58	37.46	11.54	0.53	3.82	3.61
	(244.85)	(166.99)	(14.87)	(23.23)	(22.13)	(3.08)
Invasion × Woman	−490.50***	−300.08***	−46.17***	−43.90***	−31.89***	−7.75***
	(58.28)	(36.89)	(8.31)	(13.23)	(4.88)	(2.46)
Time	1.55***	1.10***	0.13***	0.14**	0.15***	−0.03**
	(0.42)	(0.28)	(0.05)	(0.07)	(0.05)	(0.01)
Time since invasion	−9.30***	−4.44***	−0.77***	−2.28***	−0.88***	−0.02
	(0.85)	(0.48)	(0.10)	(0.19)	(0.10)	(0.03)
Intercept	321.28***	250.28***	20.12**	26.64**	14.95	5.11***
	(121.97)	(75.75)	(9.03)	(12.50)	(13.07)	(1.32)
$\hat{\sigma}_{\text{id}}$	3203.52	1935.90	205.71	316.71	323.07	21.99
$N_{Observations}$	136455	136455	136455	136455	136455	136455
$N_{Politicians}$	469	469	469	469	469	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variables are the number of respective types of reactions received by each post. The models also include random intercepts by politicians, and $\hat{\sigma}_{\text{id}}$ indicates the estimated standard deviation of the random effects. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S5.5 Reactions With Topic Controls

As another extension of the analysis of reactions in the main text, we include the topic labels as controls in the ITS model to examine whether voters are reacting differently to posts based on their topics. Topic labels are assigned at the post level, and the dependent variable is the number of certain reactions received by the post. The baseline topic is "Other." We find that the effect of war on reactions remains heterogeneous to politicians' gender after controlling for topics, and that women politicians get much less reaction than men politicians after invasion.

Table S5.4: **Effects of War on Public Reactions with Topic Controls**

	Reactions
Invasion	780.73^{***}
	(50.15)
Woman	75.99
	(235.45)
Invasion × Woman	-496.12^{***}
	(57.84)
Time	1.60^{***}
	(0.42)
Time since invasion	-9.48^{***}
	(0.86)
Social aid	-74.49^{**}
	(35.57)
Morale boost	194.02^{***}
	(52.48)
Security	-10.31
	(45.69)
Foreign affairs	-161.01^{***}
	(53.48)
Legislation	-36.00
	(36.74)
Religion	202.28^{***}
	(67.00)
Addressing Russia	170.03
	(108.13)
Intercept	302.56^{**}
	(117.46)
$\hat{\sigma}_{\text{id}}$	3069.39
$N_{Observations}$	136455
$N_{Politicians}$	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variable *Reactions* is the number of total reactions received by each post. The model also includes random intercepts by politicians, and $\hat{\sigma}_{\text{id}}$ indicates the estimated standard deviation of the random effects. The baseline category for topics is *Other*. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S5.6 Reactions With Region Controls

We add control variables on oblasts of politicians' constituencies to examine whether any spatial variation is driving the public reaction to politicians' Facebook posts. The information on politicians' oblasts is explained in detail in S3.2. Using oblasts of politicians' constituencies requires an assumption that users in an oblast will be more likely to read posts by politicians in their constituencies. Since Facebook does not provide any data on private individuals, this is the best possible measure we can implement to control for spatial variation in public reaction. The baseline category for region is "None," which includes non-MPs and MPs with national constituencies. Table S5.5 presents the result, which confirms the finding presented in the main text. The invasion makes the public engage more with politicians' post, but the rate of increase is significantly lower for women politicians.

Table S5.5: **Effect of War on Public Reactions with Region Controls**

	Reactions
Invasion	770.88^{***}
	(49.45)
Woman	-214.83
	(314.01)
Invasion × Woman	-490.76^{***}
	(58.27)
Time	1.56^{***}
	(0.42)
Time since invasion	-9.30^{***}
	(0.85)
Intercept	940.04^{***}
	(346.46)
Region controls	✓
$\hat{\sigma}_{\text{id}}$	3361.69
$N_{Observations}$	136455
$N_{Politicians}$	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variable *Reactions* is the number of total reactions received by each post. The model also includes random intercepts by politicians, and $\hat{\sigma}_{\text{id}}$ indicates the estimated standard deviation of the random effects. The baseline category for regions is *None*. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

S5.7 Reactions While Controlling for Audience Size

We examine the effect of invasion on public engagement with politicians' Facebook posts, while controlling for the potential audience size for the politicians' Facebook page. Crowdtangle API partially retains data on the number of followers of a public page when a post is created.[3] After removing posts that do not have information on the number of followers, we have 81470 posts that are written by 382 politicians, 61 women and 321 men. Then, we create a variable *Followers*, which indicate the number of followers on the politician's page when the post was created. Table S5.6 presents the results, which confirm the previous findings. Women politicians receive significantly less engagement from the public than men politicians after the invasion – even when controlling for the potential audience size.

Table S5.6: **Effect of War on Public Reactions, Controlling for Followers**

	Reactions
Invasion	832.91^{***}
	(72.97)
Woman	228.25^{**}
	(104.29)
Invasion × Woman	-555.25^{***}
	(121.69)
Time	1.24^{*}
	(0.66)
Time since invasion	-11.22^{***}
	(1.08)
Followers	0.01^{***}
	(0.00)
Intercept	90.91
	(59.67)
$\hat{\sigma}_{\text{id}}$	904.99
$N_{Observations}$	81470
$N_{Politicians}$	274

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variable *Reactions* is the number of total reactions received by each post. The model also includes random intercepts by politicians, and $\hat{\sigma}_{\text{id}}$ indicates the estimated standard deviation of the random effects. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

[3] We acknowledge that the number of followers is not an exact measure of the audience size of a post.

S5.8 Differences in Popular Posts by Men and Women Politicians

In this section, we explore whether the men's posts that get more interactions from Facebook users are different, in terms of the type and content, than the women's posts that get more reactions. To do so, we examine the top 100 most popular posts written by each gender.

For men politicians, the top 100 most popular posts were written by fifteen politicians, including one government cabinet member, four oblast governors, four mayors, and six MPs. For women, the top 100 most popular posts were also written by fifteen politicians, including one government cabinet member, one mayor, and thirteen MPs. On average, men politicians' most popular posts received 138,692.3 interactions, while women politicians' most popular posts received 35,278.46 interactions.

Table S5.7: **Popular Posts By Topics**

Topics	Social aid	Morale boost	Security	Foreign affairs	Legislation	Religion	Addressing Russia	Other
Women	5	21	16	15	6	9	8	20
Men	7	34	18	20	1	4	9	7

Note: The table entries represent the number of posts by women and men politicians that are assigned to each topic.

First, we examine whether the difference in the magnitude of interactions stem from the contents of the post. To do so, we look at the distribution of topics among the 100 most popular posts by women and men politicians. Table S5.7 presents this information. We find that popular posts tend to focus on *Foreign affairs*, *Morale boost*, and *Security*, regardless of the gender of the politicians. Recall that we identified *Morale boost* as a feminine topic and *Security* as a masculine one, with *Foreign affairs* not having clear gender connotations. It is therefore not the case that masculine topics get more interactions.

Table S5.8: **Average Sentiment Scores of Popular Posts**

	SYUZHET	NRC	BING	AFINN
Women	1.54	2.45	0.72	2.27
Men	1.02	1.60	0.93	2.24

Note: The table entries are the average sentiment scores of the top 100 popular posts by women and men politicians according to the respective lexicons.

Second, we examine whether the difference in the sentiment of the posts is associated with the difference in the level of interactions. To do so, we examine the average sentiment scores of the popular posts according to the four lexicons (SYUZHET, NRC, AFINN, BING). Table S5.8 presents the results. Overall, the scores are relatively high across the board, suggesting that popular posts seem to be expressing positive sentiments, regardless of the gender of the politician. We also don't detect systematic differences in the level of positivity of the most popular posts by women and men: the popular posts by women are more positive than the popular posts by men according to two lexicons (SYUZHET and NRC), but not according to the remaining two (BING and AFINN, although the differences here are minor). Recall also that we found that men politicians tend to use increasingly *negative*, not positive tone in response to the invasion. In short, it is not clear that the tone of the posts accounts for the higher level of popularity of men's posts.

S6 Placebo Tests

Recall from Figure 1 in the main text that there is a sudden and striking discontinuity in politicians' posting behavior right at the time of the invasion. Pre-invasion, the posting rate is relatively stable, with no increasing or decreasing trend, which would suggest any anticipation effects. Still, to more formally check whether politicians changed their behavior in anticipation of the conflict, we observe the pre-invasion data more closely and conduct several placebo tests.

First, we create a placebo cutoff at the mid-point of the pre-invasion period (December 28, 2021) to serve as our placebo treatment. This placebo treatment should not have any gendered effect on politicians' posting frequency, unless politicians started to increase or decrease their posting behavior in gendered manner in anticipation of the conflict. We run the same model as in Table 1 of the main text. The first column in Table S6.1 presents the coefficient of the interaction term for this analysis. The effect is null as expected: there is no gendered effect (in either direction) when the invasion does not take place. The remaining columns present the results for additional placebo cutoffs closer to the actual invasion: two days before (February 22), a week before (February 17) and two weeks before (February 10). The results remain consistently null on all but one of these placebo tests. We see a significant interaction coefficient on the February 10 placebo test, but it is not in the expected direction.

Table S6.1: **Placebo Invasions and Posting Behavior**

	Posts per politician			
	2021-12-28	2022-02-22	2022-02-17	2022-02-10
Invasion × Woman	0.03	0.63	0.26	0.20^{**}
	(0.04)	(0.43)	(0.17)	(0.10)
Intercept	0.71^{***}	0.58^{***}	0.60^{***}	0.65^{***}
	(0.07)	(0.06)	(0.07)	(0.07)
$N_{Observations}$	53935	53935	53935	53935
$N_{Politicians}$	469	469	469	469

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variable, *Posts per politician*, indicates the number of Facebook posts by each politician-day unit. The models include random intercepts by politician. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table S6.2, in turn, presents the results of the placebo tests for our other outcomes of interest at these same cutoffs. While some interaction effects are occasionally significant, no consistent pattern of anticipation effects emerges from the data.

Table S6.2: **Placebo Invasions and Other Outcomes**

	Sentiment				Topics			Reactions
2021-12-18	SYUZHET	NRC	BING	AFINN	Social aid	Morale boost	Security	Reactions
Invasion × Woman	−0.05	−0.16	0.20	0.01	0.02	−0.02	0.01	−2.89
	(0.12)	(0.17)	(0.23)	(0.11)	(0.01)	(0.01)	(0.01)	(114.08)
Intercept	3.46***	5.57***	4.69***	1.91***	0.19***	0.14***	0.22***	326.81***
	(0.14)	(0.20)	(0.26)	(0.12)	(0.01)	(0.01)	(0.01)	(89.90)
2022-02-22								
Invasion × Woman	−0.00	−0.25	0.01	0.21	−0.01	−0.06*	0.05*	−242.92*
	(0.20)	(0.29)	(0.38)	(0.18)	(0.03)	(0.04)	(0.03)	(143.71)
Intercept	4.21***	6.37***	6.41***	2.57***	0.16***	0.10***	0.23***	379.75***
	(0.14)	(0.20)	(0.26)	(0.12)	(0.01)	(0.01)	(0.01)	(88.60)
2022-02-17								
Invasion × Woman	0.04	−0.09	0.27	0.13	0.02	−0.04**	0.04**	−177.07*
	(0.15)	(0.21)	(0.30)	(0.14)	(0.02)	(0.02)	(0.02)	(97.97)
Intercept	4.14***	6.29***	6.31***	2.53***	0.17***	0.10***	0.22***	376.25***
	(0.14)	(0.20)	(0.26)	(0.12)	(0.01)	(0.01)	(0.01)	(89.81)
2022-02-10								
Invasion × Woman	0.12	−0.01	0.45*	0.21*	0.01	−0.02	0.02	−114.45
	(0.12)	(0.18)	(0.25)	(0.12)	(0.02)	(0.01)	(0.01)	(92.05)
Intercept	4.04***	6.13***	6.13***	2.49***	0.18***	0.11***	0.21***	364.35***
	(0.14)	(0.20)	(0.26)	(0.12)	(0.01)	(0.01)	(0.01)	(93.40)

Note: Table entries are unstandardized regression coefficients from the ITS model with Newey-West adjusted standard errors in parentheses. The dependent variables are noted in column headings. The models also include random intercepts by politicians. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

References

Angelov, Dimo. 2020. "Top2vec: Distributed representations of topics." *arXiv* .
URL: *https://doi.org/10.48550/arXiv.2008.09470*

Banco, Erin, Lara Seligman, Toosi Nahal, Ward Alexander et al. 2023. "Something Was Badly Wrong: When Washington Realised Russia Was Invading Ukraine." *Politico* .
URL: *https://www.politico.com/news/magazine/2023/02/24/russia-ukraine-war-oral-history-00083757*

Basu, Zachary. 2022. "A message from the women of Ukraine." *Axios* .
URL: *https://www.axios.com/2022/03/31/ukraine-delegation-congress-parliament*

Caprioli, Mary. 2000. "Gendered conflict." *Journal of Peace Research* 37(1):51–68.

Goldstein, Joshua S. 2001. *War and gender: How gender shapes the war system and vice-versa*. Cambridge, UK: Cambridge University Press.

Harrison, Frances. 2022. "Mobilizing masculinity: Conscription, gender, and community wellbeing in Lithuania." *Journal of International Women's Studies* 23(1):22–39.

Karmanau, Yuras. 2022. "Ukrainian leaders: Stay calm, Russian invasion not imminent." *Associated Press* .
URL: *https://apnews.com/article/russia-ukraine-russia-diplomacy-europe-baltic-sea-44821c52f54b5e927d86ea28420cb2cf*

McDowall, David, Richard McCleary and Bradley J. Bartos. 2019. *Interrupted time series analysis*. Oxford, UK: Oxford University Press.

McGlen, Nancy E and Meredith Reid Sarkees. 1993. *Women in foreign policy: The insiders*. Routledge.

Muraoka, Taishi, Jacob M. Montgomery, Christopher Lucas and Margit Tavits. 2021. "Love and anger in global party politics: Facebook reactions to political party posts in 79 democracies." *Journal of Quantitative Description: Digital Media* 1.

O'Sullivan, Mila. 2019. "'Being strong enough to defend yourself': Untangling the women, peace and security agenda amidst the Ukrainian conflict." *International Feminist Journal of Politics* 21(5):746–767.

Phillips, Sarah D and Tamara Martsenyuk. 2023. Women's agency and resistance in Russia's war on Ukraine: From victim of the war to prominent force. In *Women's Studies International Forum*. Vol. 98 Elsevier p. 102731.

Quinn, Allison. 2022. "Ukrainian defense minister: Stop the hype about a Russian invasion." *Daily Beast* .
URL: *https://www.thedailybeast.com/ukraines-defense-minister-oleksiy-reznikov-shoots-down-russian-invasion-fears*