ONLINE APPENDIX for **Nasty Politics**

The Logic of Insults, Threats, and Incitement

THOMAS ZEITZOFF[1]

[1] Associate Professor, School of Public Affairs, American University. www.zeitzoff.com

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1.1 Coding of Nasty Politics

1.1.1 Instructions to RAs

We are interested in measuring nasty politics against domestic political opponents contained in social media posts and news stories. Nasty politics includes the four different types of rhetoric, and as well as actual violence shown (See Table 1.1).

Table 1.1: Measuring threat intensity in the nasty politics in the U.S. and Ukraine

Kind of Rhetoric	**Level of Threat**	**Definition**
Insults	1	Explicitly or implicitly name-calling or insulting opponents
Accusations	2	Accusing the opponents of bad, shady, criminal, or illegal behavior. Pushing conspiracies.
Intimidating Statements	3	Intimidate, threaten, or coerce political opponents (e.g., with investigations, consequences, jail time, etc.) not in an explicitly violent manner. Veiled threats.
Incitement	4	Violent threats or encouragement violent behavior.
Physical violence	5	Includes fist fights, wrestling, choking, violent protests, melees, stabbings, and using firearms or explosives.

Domestic political opponents are broadly defined as individual politicians, political parties, partisans, police, immigrants, law enforcement businessmen, companies, journalists, judges and prosecutors, NGOs, government officials, military, minority groups, or other domestic political opponents broadly construed. Foreign groups or states don't count.

In additional to actual violence (in news stories), there are four rhetorical categories I want you to code: insults, accusations, intimidating statements, and incitement. There is a key difference between 1) insults and 2) accusations, and 3) intimidating statements and 4) incitement. Namely, 3) and 4) advocate or threaten some kind of action against domestic political opponents.

Note, many social media posts are comments or endorsements of other linked stories, images, or social media posts. So if a politician posts: "Yes–this!" and includes a link to another post or news story that contain an accusations, this would be coded as an accusation since it's endorsing an accusation. So you need to take into account the content of linked posts, stories, or images when you are coding.

1. **Name calling and insults:** Any type of rhetoric that explicitly or implicitly name-calls or insults a political opponent. It includes calling or implying that opponents dumb, stupid, idiots, corrupt, racist, assholes, terrorists, a joke, jerks, animals, scum, etc.

2. **Accusations/Conspiracy Theories**: Accusing the opponent of engaging in shady, criminal, illegal, or otherwise bad behavior. Also promulgating conspiracy theories about opponents. Note it can't just be a name-calling but must also involve an allegation of some sorts. Accusations of criminal behavior; accusations of fraud/voter fraud; accusation of Treason/Traitor; accusations of corruption/bribe; accusations of being a tool for big business or other political interests; Supporting terrorism/violence; Deep State conspiracies; Other conspiracies; Hashtags such as #StopTheSteal #BidenCrimeFamily

3. **Intimidating statements:** Statements that are design to intimidate, threaten, or coerce political opponents, not in an explicitly violent manner. Also includes veiled threats. Threatening legal action: throw someone in jail, investigate them, prosecute them. Saying they should be removed from a political office, be thrown off committees, be kicked out a party. Saying they should not be allowed to be in the legislature. Encouraging somebody to be ostracized, shunned, thrown off social media. Arguing they should be protested, mocked, or heckled Veiled threats include "Who knows what might happen" or "they better watch out"

4. **Incitement for violence:** Violent threats or encouragement violent

behavior. The key difference between intimidating statements and incitement is that with incitement there is a clear threat of real or implied violence. Advocating for opponents to beaten up, shot, threatening them with violence (violent threats). Saying they should be roughed up, eliminated, be harassed, or be scared. Again implicit threats count as well as long as there is the threat of violence behind the rhetoric. Encouragement for police or military to get physically "should take the gloves off" or "stop treating protesters so nice." Posting pictures or images of guns/weapons/crosshairs toward their opponents. Telling their supporters to come armed, or be "ready to throw down."

1.1.2 Example Coding Rules

Example A: "My opponents are weak." Coded as an INSULT

Example B: "My opponents are weak, and they are trying to sell out our country." Coded as an 1) INSULT plus an 2) ACCUSATION ("trying to sell out our the country"). **Note for something to be coded as an accusation it needs to contain an actual allegation or conspiracy theory.**

Example C: "My opponents are weak, and they are trying to sell out our country. They better watch out." Coded as an 1) INSULT plus an 2) ACCUSATION ("trying to sell out our the country") plus a 3) THREAT ("better watch out."). This is coded a threat since "better watch out" is a veiled threat–it's not explicitly violent.

Example D: "My opponents are weak, and they are trying to sell out our country. They need to eliminated." Coded as an 1) INSULT plus an 2) ACCUSATION ("trying to sell out our the country") plus 4) INCITEMENT ("need to be eliminated."). This is coded as incitement since "need to be eliminated" is a violent threat.

Table 1.2: Inter-coder reliability measure

RA #	**% Agreement**	**Cohen's κ**	**Coding Tasks**
U.S. RA #1	92%	0.830	U.S. politicians' tweets and U.S. nasty politics database
U.S. RA #2	93%	0.833	U.S. Twitter posts
U.S. RA #3	88.0%	0.756	U.S. politicians' tweet and U.S. nasty politics database
Ukraine RA #1	91.0%	0.819	Ukraine politicians' Facebook posts
Ukraine RA #2	96.6%	0.928	Ukraine politicians' Facebook posts
Ukraine RA #3	88.2%	0.717	Ukraine nasty politics database
Israel RA #1	84.0%	0.674	Israeli politicians' Twitter posts

1.1.3 Reliability of Coding

To measure reliability of coding, for each RA I had them begin their coding, by coding a subset of 100 posts or stories they coded, across the four or five (where actual violence was included as a category) categories, for 400 to 500 total coding decisions. We used this to measure percent agreement and Cohen's κ. The κ values show substantial to nearly perfect agreement.[1] See Table 1.2.

This initial coding exercise to measure agreement and inter-rater reliability, but also as a training to make sure they understood the coding. To further insure reliability, I then had my RAs highlight the few posts or stories they weren't sure how to code. We would then discuss these and come to an agreed coding.

[1] See https://idostatistics.com/cohen-kappa-free-calculator/#risultati

1.3 Chapter 3

1.3.1 Salience of Nasty Rhetoric Across Time in the U.S. 1851-2019

I searched *The New York Times* Historical Database (1851-2016) and current archive (2017-October 1, 2019) in *ProQuest.* I searched for all news articles (not opinion pieces) that were related to nasty politics at the national level. I used the following search terms:

> `united states AND congress AND (violent language OR violent rhetoric OR political insult OR political smear OR political duel OR political brawl OR political slander)`

I removed any news stories that were on foreign policy. To account for the fact that the number of news articles published by *The New York Times* has changed across years, I scaled the number of articles flagged for violent rhetoric by the total number of articles published that year. I created a yearly measure of articles containing violent rhetoric per 100,000 articles.

Note, it's best to think of Figure **??** as capturing broad trends, rather than perfectly reflective of small shifts in violent rhetoric. *The New York Times* has gone through many changes since it was known as the *New York Daily Times* in 1851 and was a staunchly Republican paper. During the late nineteenth century and early twentieth century its news coverage became less slanted, while its editorial page took on a more pro-liberal and pro-Democratic stance (Davis 1921; Diamond 1995).

1.3.2 Salience of Nasty Politics 2011-October 2019 (Media Cloud Data)

For the Media Cloud Data I used the same search terms: `united states AND congress AND (violent language, violent rhetoric, political insult, political smear, political duel, political brawl, OR political slander)`. I searched other major U.S. newspapers with different conservative and liberal slants: *USA Today, The Washington Post, New York Post, Wall Street Journal, The Boston Globe, San Francisco Chronicle, Houston Chronicle*, and *Chicago Tribune.* I created a monthly measure of violent rhetoric stories per 10,000 stories published.

1.3.3 Salience of Nasty Politics in Ukraine

To answer this question, I collected a sample of 30 examples of violent rhetoric by politicians in Ukraine across time.[2] Working with a native Russian and Ukrainian-speaking RA we used a keyword detection algorithm to

[2] These stories were both in Russian and Ukrainian.

identify initial seed words across the stories. We then used the Word2Vec algorithm (Mikolov, Sutskever, Chen, Corrado and Dean 2013) to find similar co-occurring words, and phrases, and ended with a final violent keyword corpus. See Table 1.3 for a list of words contained in the keyword corpus.

Table 1.3: Ukraine Violent Rhetoric Database Search Terms

Initial Seed Keywords in English	cattle offender litter bastard imbecile prostitute muzzle scumbag bastard robber bandit devil moron stinking ass idiot plague traitor scoundrel abomination bastard hypocritical creature ghoul devil moral fag offender sick creature idiot scarecrow pathological liar self-assured shit degenerate to threaten snake bitch prostitute a traitor immoral six scoundrel looter Judas defector hating nit drug dealer paranoid to beat shock filth
Final List of Keywords in English	cattle offender litter bastard imbecile prostitute muzzle scumbag bastard robber bandit devil moron stinking ass idiot plague traitor scoundrel abomination hypocritical creature ghoul moral fag sick creature scarecrow pathological liar self-assured shit degenerate to threaten snake bitch prostitute a traitor immoral six scoundrel looter Judas defector hating nit drug dealer paranoid to beat shock filth a criminal litter mask damn it moron rammish ass you idiot abomination hypocritical face ghoul moral fag a sick creature stuffed false pathological liar self-righteous shit immoral the six huckster he called called got into a fight scuffled liar stuffed animal turned off got his head out cut off fagots bye

The keyword corpus was translated into both Russian and Ukrainian. We then searched for "politician" + "[final violent keyword corpus]" to identify variation across time in violent rhetoric in different Ukrainian media sources.

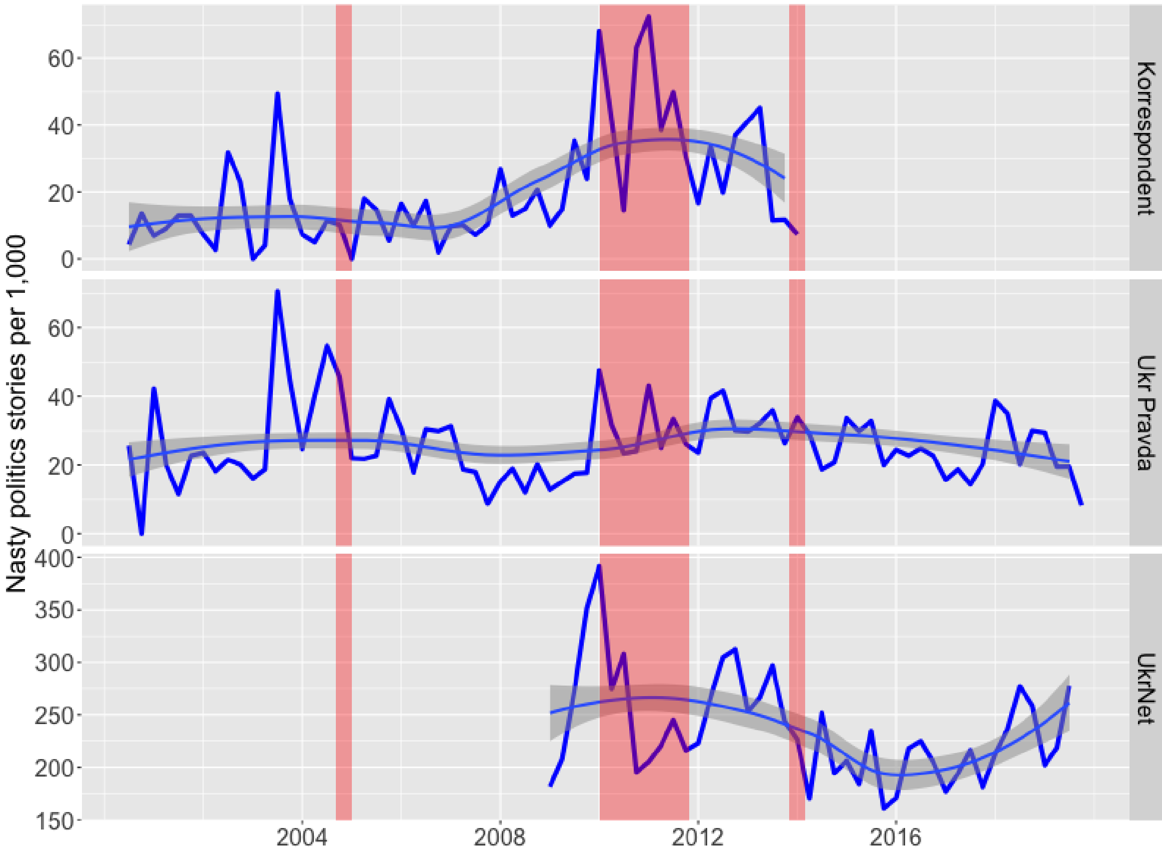
One of the difficulties in measuring violent rhetoric in the Ukrainian media is the fact that there does not exist one single authoritative news source, such as *The New York Times*, and the fact that much of the media is controlled (at least tacitly) by oligarchs.[3] To deal with this, I used three different sources to put together data on the presence of violent rhetoric in the media in Ukraine from 2001-October 1, 2019: the pro-Russian/pro-Yanukovych website *Korrespondent*, the pro-Ukrainian website *Ukrayinska Pravda*, and the news aggregator *Ukr.net*. It should be noted that *Ukr.net* does not begin until October 2009. Also, I stop using the *Korrespondent* time series in February of 2014, when one of its founders, Serhiy Kurchenko, fled Ukraine to Russia following the ousting of Yanukovych when there was a warrant out for his arrest.[4] Following Kurchenko's exile, the coverage of *Korrespondent* political section dramatically changed.[5]

[3] See https://www.atlanticcouncil.org/blogs/ukrainealert/will-ukraine-s-oligarchs-ever-get-challenged/

[4] See https://www.kyivpost.com/ukraine-politics/ukrainian-court-rules-arrest-fugitive-businessm html.

[5] See https://www.kyivpost.com/ukraine-politics/2013-ukraine-ignites-in-revolution-to-seize-con html.

Figure 1.1: Violent Rhetoric Across Time in Ukraine Disaggregated (2001-October 1, 2019).



Red shaded spikes correspond to the Orange Revolution (2004-2005), the trial of former Prime Minister Yulia Tymoshenko (2010-2011), and the Euromaidan Revolution (2013-2014). Sources include *Ukrayinska Pravda*, *Ukr.net*, and *Korrespondent*.

1.3.4 Salience of Nasty Politics in Israel

To measure the salience of nasty politics in Israel, I searched articles from *Ynet* (ynet.co.il). *Ynet* is the most popular news site in Israel, and the fifth most visited website behind Facebook.[6] I counted all articles from 2001-July 2020 using Google Site Search. Search terms include `Knesset AND (traitor OR liar OR insult OR ‘‘violent rhetoric,’’ ‘‘smear,’’ ‘‘slander’’ OR ‘‘incitement’’)`. The base comparison, or denominator was stories on *Ynet* containing the word "news." This gives us a yearly measure of nasty politics stories per 1,000 news stories.

1.3.5 Additional Results

Table 1.4: Tweets from U.S. politicians with higher threat intensity, or that are nasty, get more engagement during the beginnings of the COVID crisis and Black Lives Matter protests in 2020 (OLS)

	Dependent variable:			
	log(Retweet Count + 1)		log(Favorite Count + 1)	
	(1)	(2)	(3)	(4)
Intensity	0.231***		0.181***	
	(0.006)		(0.008)	
Nasty		0.871***		0.699***
		(0.022)		(0.027)
Fixed Effects	✓	✓	✓	✓
Observations	15,635	15,635	9,669	9,669
R^2	0.499	0.503	0.542	0.546
Adjusted R^2	0.499	0.502	0.541	0.545

Note: *p<0.1; **p<0.05; ***p<0.01 Controls for whether a Tweet was a retweet. Fixed effects for politicians The variable Intensity is a continuous measure of threat intensity of the tweet, while the Nasty variable is a dummy variable for whether a tweet contains any type of nasty rhetoric (insult, accusation, intimidation, or incitement).

[6] See https://www.alexa.com/topsites/countries/IL

Table 1.5: Higher threat intensity of Facebook posts get more engagement during 2019 Ukrainian election period (OLS)

	Dependent variable:			
	log(Likes + 1)	log(Comments + 1)	log(Shares + 1)	log(Angry + 1)
	(1)	(2)	(3)	(4)
Intensity	0.029***	0.129***	0.129***	0.208***
	(0.007)	(0.010)	(0.009)	(0.011)
Fixed Effects	✓	✓	✓	✓
Observations	2,655	2,655	2,655	2,655
R^2	0.707	0.664	0.510	0.521
Adjusted R^2	0.707	0.663	0.509	0.520
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 1.6: Higher threat intensity of Facebook posts get more engagement during 2019 Ukrainian election period (OLS)

	Dependent variable:				
	log(Love + 1)	log(Wow + 1)	log(Haha + 1)	log(Sad + 1)	log(Care + 1)
	(1)	(2)	(3)	(4)	(5)
Intensity	0.036***	0.079***	0.145***	0.098***	0.0002
	(0.009)	(0.008)	(0.011)	(0.012)	(0.001)
Fixed Effects	✓	✓	✓	✓	✓
Observations	2,655	2,655	2,655	2,655	2,655
R^2	0.731	0.568	0.427	0.225	0.076
Adjusted R^2	0.730	0.567	0.425	0.223	0.074
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 1.7: Nasty Facebook posts get more engagement during 2019 Ukrainian election period (OLS)

	Dependent variable:			
	log(Likes + 1)	log(Comments + 1)	log(Shares + 1)	log(Angry + 1)
	(1)	(2)	(3)	(4)
Nasty	0.080**	0.559***	0.596***	1.015***
	(0.037)	(0.056)	(0.047)	(0.061)
Fixed Effects	✓	✓	✓	✓
Observations	2,656	2,656	2,656	2,656
R^2	0.706	0.658	0.500	0.511
Adjusted R^2	0.705	0.657	0.499	0.510
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 1.8: Nasty Facebook posts get more engagement during 2019 Ukrainian election period (OLS)

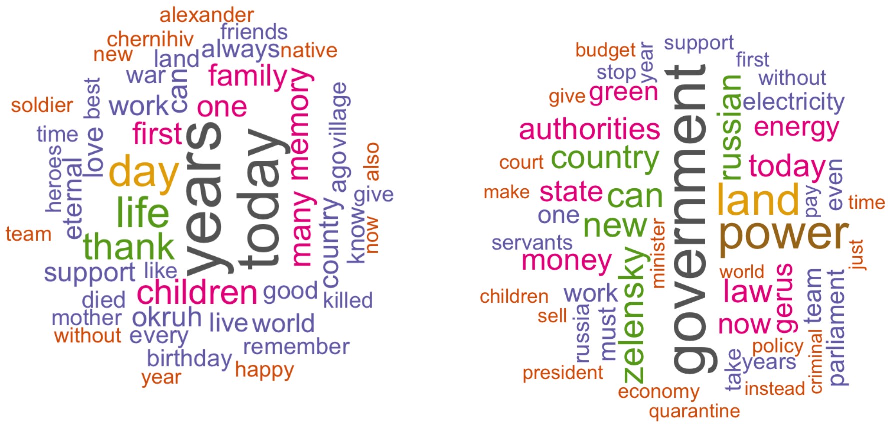
	Dependent variable:				
	log(Love + 1)	log(Wow + 1)	log(Haha + 1)	log(Sad + 1)	log(Care + 1)
	(1)	(2)	(3)	(4)	(5)
Nasty	0.087^{*}	0.375^{***}	0.755^{***}	0.446^{***}	-0.003
	(0.046)	(0.041)	(0.060)	(0.067)	(0.008)
Fixed Effects	✓	✓	✓	✓	✓
Observations	2,656	2,656	2,656	2,656	2,656
R^2	0.730	0.564	0.425	0.220	0.076
Adjusted R^2	0.729	0.563	0.424	0.218	0.074
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 1.9: Tweets from Israeli politicians with higher threat intensity, or that are nasty, get more engagement during the beginnings of the COVID crisis and anti-Netanyahu protests in 2020 (OLS)

	Dependent variable:			
	log(Retweet Count + 1)		log(Favorite Count + 1)	
	(1)	(2)	(3)	(4)
Intensity	0.156^{***}		0.104^{***}	
	(0.008)		(0.008)	
Nasty		0.667^{***}		0.475^{***}
		(0.026)		(0.028)
Fixed Effects	✓	✓	✓	✓
Observations	5,274	5,277	4,648	4,651
R^2	0.491	0.512	0.279	0.297
Adjusted R^2	0.490	0.511	0.278	0.296

Note: *p<0.1; **p<0.05; ***p<0.01 Controls for whether a Tweet was a retweet. Fixed effects for politicians The variable Intensity is a continuous measure of threat intensity of the tweet, while the Nasty variable is a dummy variable for whether a tweet contains any type of nasty rhetoric (insult, accusation, intimidation, or incitement).

Figure 1.2: Word Clouds of Lyashko Non-Nasty vs. Nasty Facebook Posts (August 1, 2019-October 31, 2020).



(a) Non-Nasty Posts

(b) Nasty Posts

Table 1.10: Higher threat intensity of Lyashko's Facebook posts get more engagement August 1, 2019-November 1, 2020 (OLS)

	Dependent variable:			
	log(Likes + 1)	log(Comments + 1)	log(Shares + 1)	log(Angry + 1)
	(1)	(2)	(3)	(4)
Intensity	−0.001	0.048***	0.098***	0.218***
	(0.009)	(0.013)	(0.010)	(0.013)
Observations	1,233	1,233	1,233	1,233
R^2	0.00000	0.011	0.074	0.181
Adjusted R^2	−0.001	0.010	0.074	0.180
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 1.11: Higher threat intensity of Lyashko's Facebook posts get more Wows, Hahas, and Sad Faces, but fewer Care and Love reactions August 1, 2019-November 1, 2020 (OLS)

	Dependent variable:				
	log(Love + 1)	log(Wow + 1)	log(Haha + 1)	log(Sad + 1)	log(Care + 1)
	(1)	(2)	(3)	(4)	(5)
Intensity	-0.078^{***}	0.085^{***}	0.125^{***}	0.042^{**}	-0.028^{***}
	(0.015)	(0.010)	(0.014)	(0.019)	(0.009)
Observations	1,233	1,233	1,233	1,233	1,233
R^2	0.020	0.056	0.057	0.004	0.008
Adjusted R^2	0.020	0.056	0.056	0.003	0.007
Note:	*p<0.1; **p<0.05; ***p<0.01				

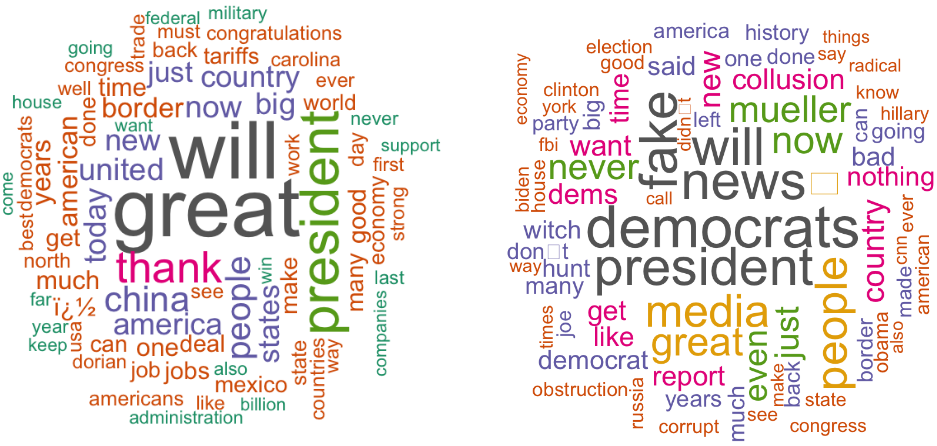
Table 1.12: Lyashko's Nasty Facebook posts get more engagement, but less likes August 1, 2019-November 1, 2020 (OLS)

	Dependent variable:			
	log(Likes + 1)	log(Comments + 1)	log(Shares + 1)	log(Angry + 1)
	(1)	(2)	(3)	(4)
Nasty	-0.115^{**}	0.173^{**}	0.547^{***}	1.237^{***}
	(0.046)	(0.069)	(0.053)	(0.070)
Observations	1,234	1,234	1,234	1,234
R^2	0.005	0.005	0.079	0.202
Adjusted R^2	0.004	0.004	0.078	0.201
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 1.13: Lyashko's Nasty Facebook posts get more Wows, Hahas, and Sad Faces, but fewer Care and Love reactions August 1, 2019-November 1, 2020 (OLS)

	Dependent variable:				
	log(Love + 1)	log(Wow + 1)	log(Haha + 1)	log(Sad + 1)	log(Care + 1)
	(1)	(2)	(3)	(4)	(5)
Nasty	-0.727^{***}	0.430^{***}	0.623^{***}	0.267^{***}	-0.200^{***}
	(0.081)	(0.053)	(0.078)	(0.103)	(0.048)
Observations	1,234	1,234	1,234	1,234	1,234
R^2	0.062	0.050	0.050	0.005	0.014
Adjusted R^2	0.061	0.049	0.049	0.005	0.013
Note:	*p<0.1; **p<0.05; ***p<0.01				

Figure 1.3: Word Clouds of Trump's Non-Nasty vs. Nasty Tweets (April 15, 2019-October 3, 2019).



(a) Non-Nasty Tweets

(b) Nasty Tweets

Table 1.14: Donald Trump's that score higher in Intensity, or are coded as Nasty or not, get more engagement.

	Dependent variable:			
	log(Retweet Count)		log(Favorite Count)	
	(1)	(2)	(3)	(4)
Intensity	0.078***		0.028***	
	(0.006)		(0.005)	
Nasty		0.246***		0.083***
		(0.018)		(0.018)
Observations	3,501	3,501	2,294	2,294
R^2	0.342	0.341	0.075	0.073
Adjusted R^2	0.341	0.341	0.074	0.072

Note: *p<0.1; **p<0.05; ***p<0.01 Controls for whether a Tweet was quote tweeted or a retweet. The variable Intensity is a continuous measure of threat intensity of the tweet, while the Nasty variable is a dummy variable for whether a tweet contains any type of nasty rhetoric (insult, accusation, intimidation, or incitement).

1.4 Chapter 4

1.4.1 Mass Surveys in Ukraine and U.S. October-November 2018

The first Ukraine survey (N=1,030) was a module that was part of a face-to-face omnibus survey carried out by the Kyiv International Institute for Sociology (KIIS) from October 27-November 9, 2018. The U.S. data was collected via Amazon Mechanical Turk (MTurk) in early November 2018.[7] 494 respondents completed the survey but 37 respondents were dropped for using virtual private servers (VPSs), or whose IP address indicated that were outside the US for a total N=457.[8]

Acceptability of different Rhetoric (Fall 2018

During the survey each respondent saw and rated six different examples of nasty rhetoric. It was presented in the form of "a politician said the following about their political opponent":

"They're a thief." (Insult and accusation example)

OR

"They should be harassed on social media." (Incitement example)

They were then asked how acceptable, how violent, how threatening, and how disgusting they found this type of speech.[9]

480 respondents in the U.S. answered the survey collected via Amazon's MTurk in mid-December 2019. Respondents were paid $0.75 for a brief 4-6 minute survey. 520 respondents started the survey but 40 respondents were dropped for using virtual private servers (VPSs), or whose IP address indicated that were outside the US for a total N=480. Identifying those using VPSs or who had IP addresses that were known to cause issues was done using the technique in Kennedy et al. (2018). In the U.S. survey respondents were randomly assigned to three different vignette experiments such that approximately 400 of the 480 respondents were in each vignette. I present results from each of the vignette experiments below. I also included an attention check which 95% of respondents passed. "Many people get their news from various sources, these include radio, local TV, national TV, social media, friends, and family, and other sources. Please check all the sources where you get your news from. To show that you have read the question fully, regardless of where you get your news from just select local TV and

[7] Respondents were paid $0.60 for a brief 5-7 minute survey.

[8] Identifying those using VPSs or who had IP addresses that were known to cause issues was done using the technique in Kennedy et al. (2018).

[9] For the purposes here I focus on the level of acceptability. But Cronbach's α in the U.S. (0.84) and in Ukraine (0.85) suggest that acceptability, violent, threat, and disgust perceptions are positively correlated and picking up similar variation.

Table 1.15: Sample Characteristics National Ukraine Survey (October-November, 2018)

Age	18-29 13.5% 30-44 28.9% 45-59 27.9% 60+ 29.7%
Gender	Male 39.8%
Education	65.1% completed secondary school and have vocational, or some higher education
Views on Maidan	48% supporters of Maidan
Language	Ukrainian 49.9% Russian 38.6% Mix of Ukrainian Russian 11.5%
Region	West 27.6% Center 35.3% South 11.2% East 19.4% Donbas 6.5%

Table 1.16: Sample characteristics US MTurk survey (November 2018)

Age	18-29 29.3% 30-44 45.5% 45-59 18.8% 60 + 6.6%
Partisanship	37% Republican
Gender	45.7% Male
Race	75.6% non-Hispanic White
Education	51% Have graduated college or have a graduate degree

other. Yes, ignore the question and just select these two options instead." Restricting respondents to simply those 455 who passed the attention check does not change any of the results presented here.

Table 1.17: Sample characteristics national KIIS Ukraine survey (September 2019)

Age	18-29 13.2% 30-44 24.7% 45-59 28.2% 60+ 33.9%
Gender	Male 40.4%
Education	75.3% completed secondary school and have vocational, or some higher education
Views on Maidan	48.6% supporters of Maidan
Support Zelensky	76% strongly or somewhat support President Zelensky
Language	Ukrainian 54.2% Russian 41.0% Mix of Ukrainian Russian 4.8%
Region	West 27.7% Center 34.3% South 24.7% East 7.0% Donbas 6.3%

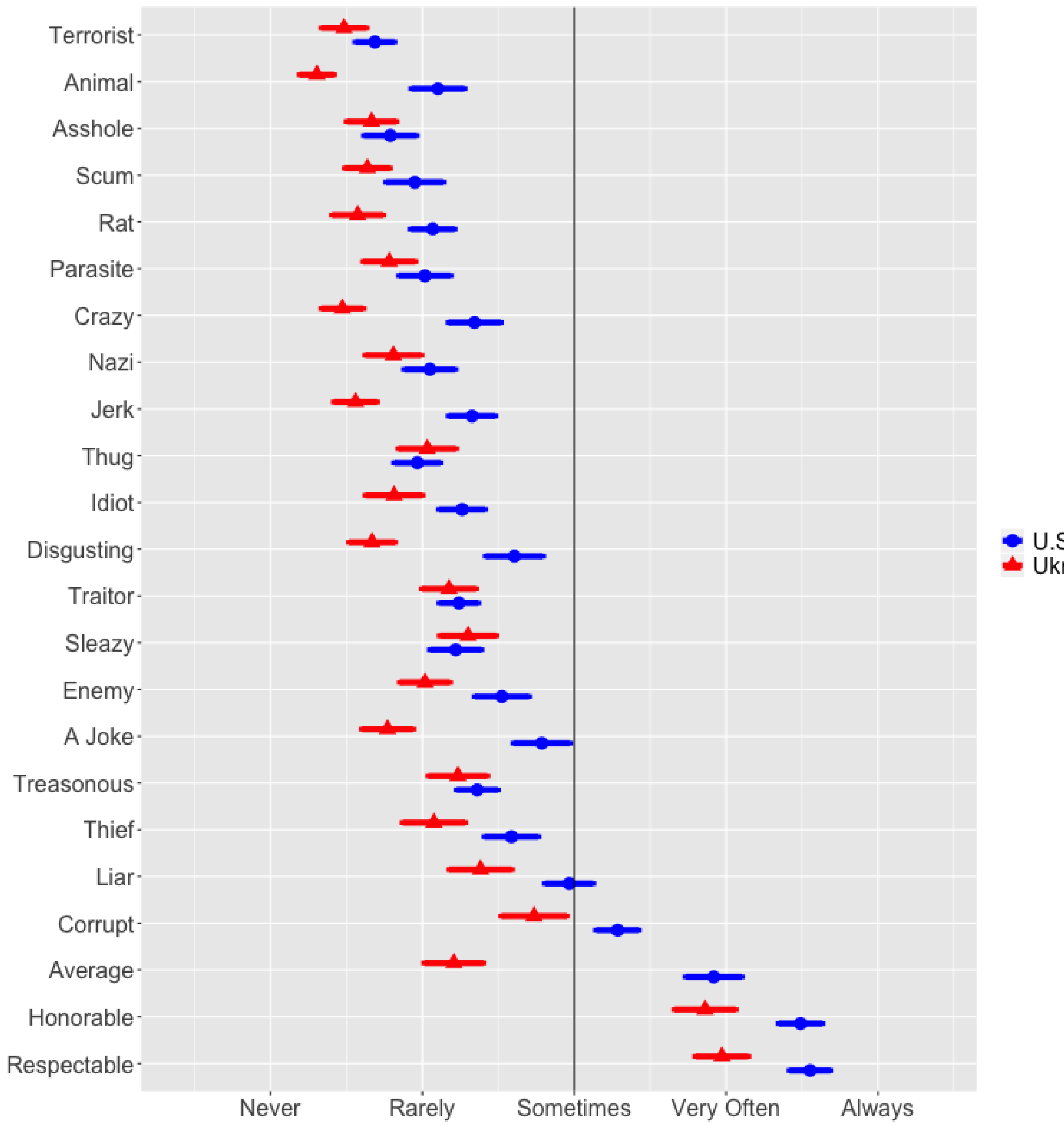
Table 1.18: Sample characteristics US MTurk survey (December 2019)

Age	18-29 29.2% 30-44 47.5% 45-59 17.7% 60 + 5.4%
Partisanship	35.2% Republican
Gender	57% Male
Race	71.3% non-Hispanic White
Education	56.1% Have graduated college or have a graduate degree

Table 1.19: Sample characteristics national Ukraine KIIS survey (February 2020)

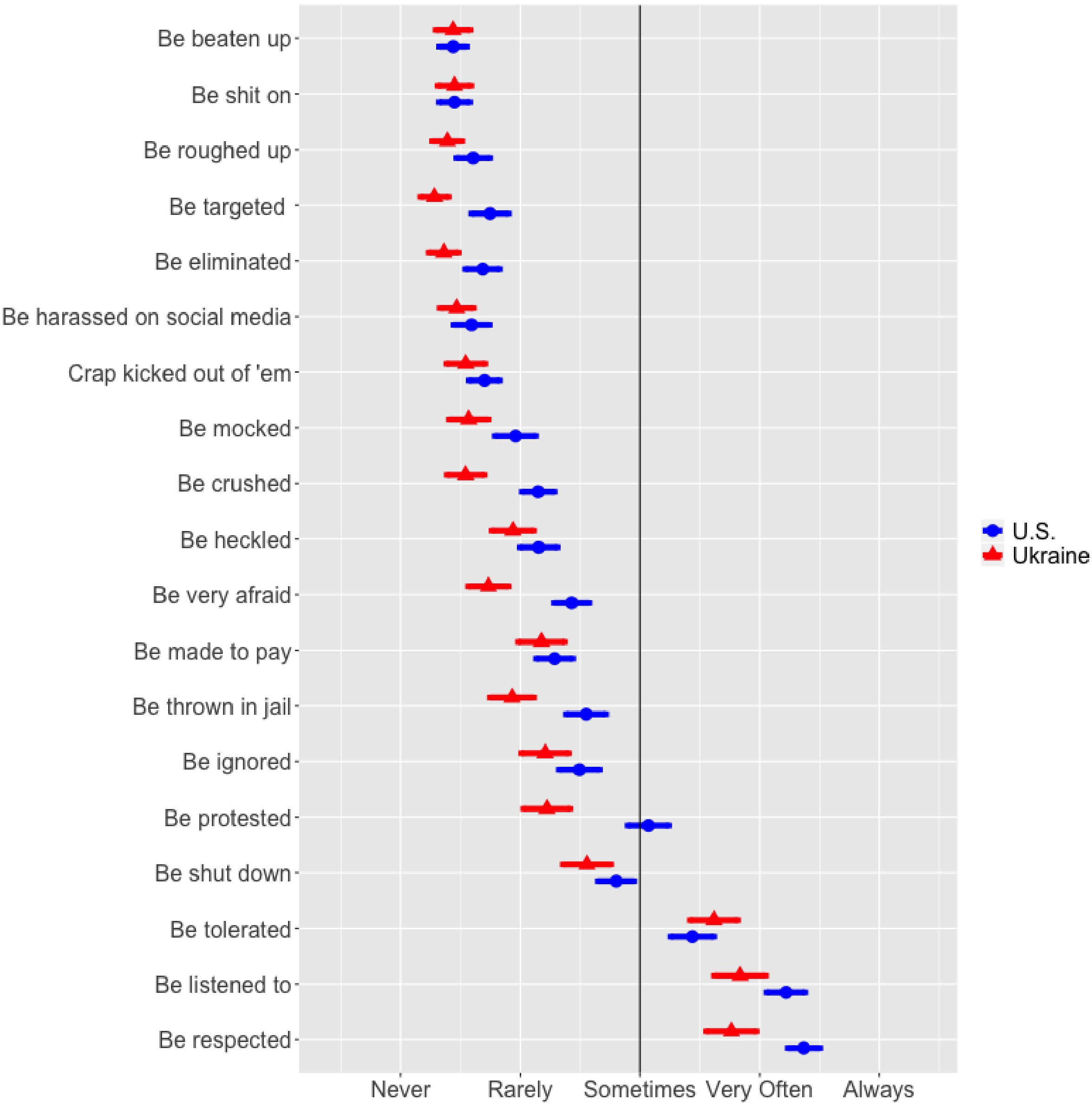
Age	18-29 13.9% 30-44 22.6% 45-59 27.1% 60+ 36.4%
Gender	Male 42.4%
Education	71.9% completed secondary school and have vocational, or some higher education
Views on Maidan	47.9% supporters of Maidan
Language	Ukrainian 51.3% Russian 41.9% Mix of Ukrainian Russian 6.8%
Region	West 28.0% Center 34.0% South 24.2% East 7.6% Donbas 6.3%

Figure 1.4: Wide variation in the perceived acceptability of different insults and accusation in the U.S. and Ukraine (Unweighted Data)



Means with associated 95% Confidence Intervals

Figure 1.5: Intimidating statements and incitement are mostly viewed as unacceptable in the U.S. and Ukraine.



Means with associated 95% Confidence Intervals

Table 1.20: Personality Correlates of Support for Violent Rhetoric (U.S. MTurk Sample, Unweighted Data)

	Dependent variable: General Acceptance of Violent Rhetoric (0-1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tough Leader	0.068***						0.054***
	(0.017)						(0.019)
Authoritarian		0.008					-0.002
		(0.016)					(0.017)
Aggression			0.084***				0.053*
			(0.025)				(0.027)
Social Dominance				0.070***			0.021
				(0.023)			(0.028)
Violence Justified					0.087***		0.047
					(0.027)		(0.029)
Republican						0.020*	-0.001
						(0.012)	(0.013)
Constant	0.394***	0.413***	0.397***	0.397***	0.403***	0.408***	0.375***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.011)
Observations	457	457	457	457	457	457	457
R^2	0.034	0.001	0.024	0.020	0.022	0.006	0.059
Adjusted R^2	0.031	-0.002	0.022	0.017	0.019	0.004	0.046

Note: *p<0.1; **p<0.05; ***p<0.01. October 2018 Amazon MTurk survey

1.4.2 Treatment Wordings Experiment 1 and 2

Table 1.21: Experiment 1: Example threatening rhetoric treatments for a Democrat respondent in the U.S. and Euromaidan supporter in Ukraine

Nasty Rhetoric (U.S.)	Representative A is a Democratic member of Congress and posted the following on their social media page: "Democrats need to stop electing 'nice guys.' We need street fighters to deal with some of these Republican assholes."
Nasty Rhetoric + Want to Destroy Us (U.S.)	Representative A is a Democratic member of Congress and posted the following on their social media page: "Democrats need to stop electing 'nice guys.' We need street fighters to deal with some of these Republican assholes. Republicans don't just want to win, they want to destroy us."
Nasty Rhetoric (Ukraine)	Politician A is a member of the Rada and supporter of Euromaidan. Politician A posted the following on their social media page: "Supporters of Euromaidan need to stop electing 'nice guys.' We need street fighters to deal with some of these pro-Russian asshole politicians."
Nasty Rhetoric + Want to Destroy Us (Ukraine)	Politician A is a member of the Rada and supporter of Euromaidan. Poltician A posted the following on their social media page: "Supporters of Euromaidan need to stop electing 'nice guys.' We need streetfighters to deal with some of these pro-Russian asshole politicians. Pro-Russian politicians don't just want to win, they want to destroy us."

Note: Republicans and Euromaidan opponents saw the exact same vignettes, with the group names changed to match their political identity.

Table 1.22: Experiment 2: Example high and low threat treatments for a Democrat respondent in the U.S. and a Euromaidan supporter in Ukraine.

Low Threat (U.S.)	Several right-wing activists held signs silently protesting outside the headquarters of the Democratic Party. After the protests two Democrats running for the same Congressional seat said the following to reporters: Candidate A: "I wish we could all just get along." Candidate B: "Some of these Republicans are animals who deserve to be roughed up."
High Threat (U.S.)	Several right-wing activists threw Molotov cocktails through the windows of the headquarters of the Democratic Party. After the attack two Democrats running for the same Congressional seat said the following to reporters: Candidate A: "I wish we could all just get along." Candidate B: "Some of these Republicans are animals who deserve to be roughed up."
Low Threat (Ukraine)	Several pro-Russian activists held signs silently protesting outside the headquarters of a Pro-Euromaidan political party. After the protest, two politicians from this same Pro-Euromaidan political party that are running against each other for the Rada said the following to reporters: Candidate A: "I wish we could all just get along." Candidate B: "Some of these pro-Russian supporters are animals who deserve to be beaten up."
High Threat (Ukraine)	Several pro-Russian activists threw Molotov cocktails through the windows of the headquarters of a Pro-Euromaidan political party. After the attack, two politicians from this same Pro-Euromaidan political party that are running against each other for the Rada said the following to reporters: Candidate A: "I wish we could all just get along." Candidate B: "Some of these pro-Russian supporters are animals who deserve to be beaten up."

Note: Republicans and Euromaidan opponents saw the exact same vignettes, with the group names changed to match their political identity.

1.5 Chapter 5

1.5.1 U.S. and Ukraine Violent Database

Ukrainian Database

To create the database in Ukraine, I first worked with my Russian and Ukrainian research assistants to put together an initial dataset of 27 different examples of violent rhetoric and fights from the across the Ukrainian political spectrum. We used these initial stories to create the seed search terms that are shown in Table 1.3. We then used these initial seed search terms to find other words using *word2vec*. Word2vec is a neural network who's fundamental assumption is that words with similar meanings are likely to co-occur in similar contexts (Mikolov et al. 2013). So stories about "jerks" are more likely to also mention "jackasses." We used our seed of 50 terms and initial corpus dataset to identify a final list of 76 terms. We then put together a database of 829 politicians. These include:

1. All politicians from the eighth Rada (2014-June 2019)

2. All politicians the ninth Rada (August 29, 2019-present)

3. All presidential candidates from the 2019 presidential candidates

4. The top 10 candidates of the top 15 parties from the 2019 Rada elections. I also included the center-right Self-Reliance and far-right *Svoboda* parties.

We then used this full list of politicians and final list of search terms to search for new examples of violent rhetoric (in both Ukrainian and Russian) on the following seven news websites: 1) `znaj.ua`, 2) `ukr.net`, 3) `obozrevatel.com`, 4) `politeka.net`, 5) `korrespondent.net`, 6)`tsn.ua`, and 7) `segodnya.ua` from January 1, 2016-October 1, 2019. These website are the largest media and news sites in Ukraine and have excellent coverage, especially since `ukr.net` is a news aggregator and links to other websites.[10] This was designed to make the database as inclusive as possible (allowing a lot of false positives) and minimize the number of missing stories (false negatives). The database contained over 3,283 unique URLs. My RAs went through the database and deleted duplicates or stories that were not relevant (e.g., about foreign policy), and we were left with a database of 339 events. Note that if two politicians got into a fight or war of words, this was counted as two events–and I included what Politician A said to Politician B as one observation, and what Politician B said to Politician A as another.

[10]See `https://www.similarweb.com/top-websites/ukraine/category/news-and-media` and `https://www.allyoucanread.com/ukrainian-newspapers/`

U.S. Database

To construct the U.S. database, I followed a similar strategy. I identified 46 seed stories of national politicians—House, Senate, and presidential candidates, and office-holders–who had engaged in name-calling, threats, or actual physical violence as in the case of Montana Republican Congressional Greg Gianforte who assaulted a reporter in May 2017.[11] I used the TextRank keyword algorithm detection algorithm to extract commonly shared words and phrases across news stories. The keywords are shown in Table 1.23. The initial keywords were those that were extracted from the TextRank algorithm. However, I pruned this list and removed common words such as "American," "our country," and "political." I also added words that are associated with nasty style including "insult," "smear," "name calling," and "political attack."

Table 1.23: U.S. Violent Rhetoric Database Search Terms

Initial List	social media, twitter, tweet, supporters, attack political attack, white nationalis, white supremacist, right wing, left wing, fake news, news media, illegal, news conference, American, our country, calling, name calling, racis, political
Final List of Keywords	violent rhetoric, tweeted, insult, smear, political attack, threaten, white nationalis, white supremacist, right wing, left wing, fake news, name calling, racis

I used these terms to search LexisNexis news database from January 1, 2016- October 1, 2019. I focused on five websites: 1) nytimes.com (*The New York Times*), 2) washingtonpost.com (*The Washington Post*), 3) cnn.com (*CNN*), 4) politico.com (*Politico*), and 5) mailonline.com (*The Daily Mail*). I then selected the "Negative Personal News" feature within LexisNexis to further refine the results. "The Negative Personal News uses an extensive that classification system then identifies and delivers documents with a significant level of negative language."[12] The following was the search criteria:

```
united states AND congress AND (‘‘violent rhetoric’’ OR ‘‘tweeted’’
OR ‘‘insult’’ OR ‘‘smear’’ OR ‘‘political attack’’ OR ‘‘threaten’’
OR ‘‘white nationalis’’ OR ‘‘white supremacist’’ OR ‘‘right
```

[11] See https://www.buzzfeednews.com/article/alexislevinson/reporter-alleges-that-republican-candidate-body-slammed-him

[12] See https://www-lexisnexis.com./infopro/keeping-current/b/weblog/archive/2019/03/06/quickly-find-negative-news-on-companies-and-individuals-on-lexis-advance.aspx

`wing'' OR ``left wing'' OR ``fake news'' OR ``name calling'' OR ``racis'')`

There were 2,536 stories returned. My RAs then went through each story removing duplicates, stories about foreign policy, and those that were simply not relevant for 1,407 instances (including the initial seed stories) of nasty rhetoric.

1.6 Chapter 6: Elites

1.6.1 Elite Samples

Table 1.24: Summary statistics of KIIS elite Ukraine survey (March-April, 2019)

Age	18-29 32.7% 30-44 43.6% 44-59 23.6% 60+ 3.1%
Gender	Male 52.7%
Position	Member of a local NGO 50.9% Member of National NGO 20.0% Member of an Int'l NGO 3% Politician (local politics) 15.2% Politician (national politics) 2.4% Political consultant 12% Journalist/activist 1.2%
Views on Maidan	69.7%Maidan supporters
Language	Ukrainian 37.6% Russian 37.6% Mix of Ukrainian and Russian 24.8%
Region	West 13.9% Center 45.5% South 21.8% East 12.1% Donbas 6.5%

Table 1.25: Summary statistics CivicPulse elite U.S survey (March-April, 2019)

Age	21-55 21.5% 56-70 43.8% 71-95 26% Didn't say 8.7%
Gender	72.1% Male
Education	Have graduated college or have a graduate degree%
Race	85.3% Non-Hispanic White
Republican	47%
Type of Government	County 14.7% Municipal 65.3% Township 19.6%
Elected official	94%
Average Gov't Experience	14 years
Census Region	Midwest 38.1% Northeast 24.7% South 20.6% West 16.4%

Table 1.26: Demographics of elite in-depth interviews (March 2018-April, 2020)

	Ukraine (N=38)	**U.S.** (N=21)
Position		
	Academic 2.6% Activist 18.4% Campaign Strategist 21.1% Journalist 18.4% Party Activist 39.5%	Academic 4.8% Activist 4.8% Campaign Strategist 81.0% Journalist 9.5% Party Activist 0%
Partisanship		
	Anti-Maidan (general) 8.6% Center Right 2.9% Leftist 5.7% Lyashko 5.7% Far Right 11.4 Poroshenko supporter 5.7% Pro-Maidan (general) 28.6% Tymoshenko 11.4% Pro-Russian 11.4% Zelensky 11.4%	Mainstream Democrat 52.4% Republican 28.6% Leftist/Bernie 19.0%

Table 1.27: Summary statistics of expert survey of political scientists N=180 (Spring 2021)

Position	Grad Student 12.2% Post Doc 5% Faculty Non-Tenure Track 2.2% Assistant Professor 38.9% Associate Professor 22.2% Full Professor 16.7%
Field	Comparative 34% IR 26.7% American 25.6% Political Communication 7.2% Methods 1.7% Other 3.3%
Specialty*	Political Violence 46.1 % Political Psychology 31.1% Political Behavior 55.6% Institutions 31.7% Social Media 20.6% Political Economy 17.8% Race and Ethnic Politics 18.9%

*Non-mutually exclusive

1.6.2 Additional Plots from Political Science Sample

Figure 1.6: Most political scientists view incitement as quite threatening. Intimidation are also viewed as quite threatening. Accusations and insults have a wider variation. (N=180)

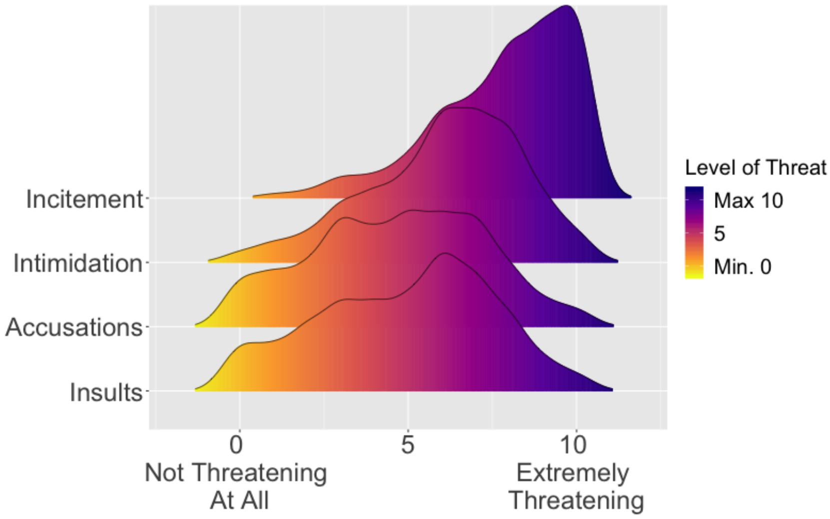
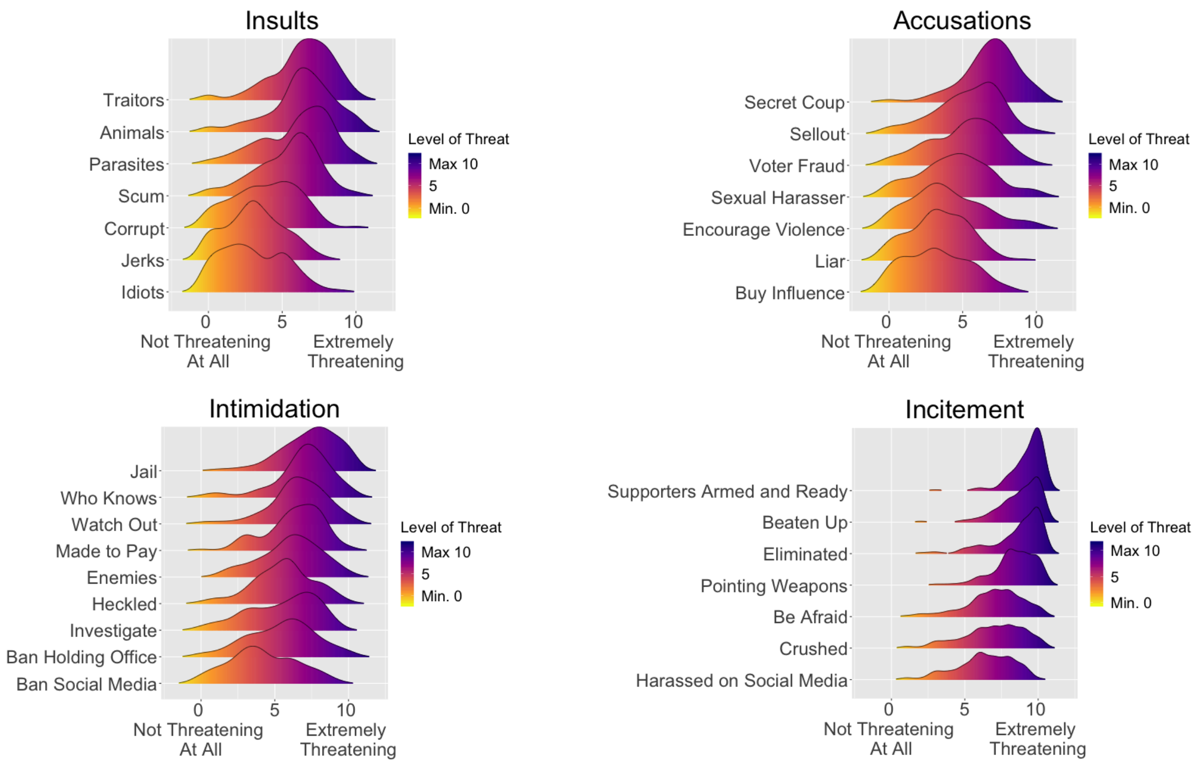


Figure 1.7: Most political science agree different types of incitement are threatening. There's less agreement on intimidation, accusations, and insults. (N=180)



1.7 Chapter 7: Surveys in Israel, Ukraine, and the U.S.

1.7.1 Sample Characteristics

The U.S. survey was carried out on the LUCID[13] platform in late October 2020. I dropped respondents that did not pass the three initial attention checks:

1. Do you agree to participate? (Yes/No)

2. For our research, paying close attention to survey questions is important! We appreciate your close attention. (I understand/I do not understand)

3. People are very busy these days and many do not have time to follow what goes on with current events . We are testing whether people read all of the questions. To show that you've read this much, answer both "excellent" and "good" (Excellent, Good, Average, Poor, and Terrible).

This led to 541 respondents being dropped.[14] Respondents who didn't complete more than 50 percent of the survey (25 dropped), and those that sped through the survey less than 3 and half minutes, 16 respondents.

For the Israel online survey I dropped any respondent that did not pass the same initial attention checks as the LUCID survey (78 respondents), and I also dropped those who didn't complete more than 50 percent of the survey (66 respondents).

Note in both Israel and U.S. I also included a more demanding attention check:

> Many people get their news from various sources, these include radio, local TV, national TV, social media, friends, and family, and other sources. Please check all the sources where you get your news from. To show that you have read the question fully, regardless of where you get your news from, select websites and social media. Yes, ignore the question and just select these two options instead. (Radio, Local TV, National TV, Websites, Social Media, Friends and Family, and Others)

67% of the Israeli iPanel respondents passed it, and 57% of the U.S. LUCID panel passed it. When I run the results presented only on those who passed the more demanding attention check, the results do not change.

[13] https://luc.id/

[14] This is as recommended in "Evidence of Rising Rates of Inattentiveness on Lucid in 2020" by Peter Aronow, Joshua Kalla, Lilla Orr, and John Ternovski at https://osf.io/preprints/socarxiv/8sbe4/

Table 1.28: Sample characteristics US LUCID Survey N=1,399 (October 2020)

Age	18-29 17.7% 30-44 30.3% 45-59 24% 60 + 28%
Partisanship	45.6% Republican
Vote Choice 2020	Donald Trump 39.6% Joe Biden 49.4% Undecided 8.5% Other 2.5%
Gender	48.2% Male
Race	73.4% non-Hispanic White
Education	53% Have graduated college or have a graduate degree

Table 1.29: Sample characteristics Israel iPanel online Jewish sample N=1,342 (September, 2020)

Gender	
	Male 51.6%
Age	
	18-22 12.9%
	23-29 17.8%
	30-39 21.3%
	40-49 17.3%
	50-70 30.7%
Ethnicity	
	Ashkenazi 34.4%
	Ethiopian 0.4%
	Mixed 17.6%
	Mizrahi 39.1%
	Russian 5.3%
	Other 3.3%
Religiosity	
	Secular 43.7%
	Traditional 35.9%
	Religious 11.0%
	Haredi 9.5%
Locality	
	Jerusalem 11.2%
	North 29.7%
	Sharon 7.70%
	South 21.6%
	Tel Aviv 29.7%
Education	
	Bachelor Degree or Higher 43.3%
Ideology scale	
	Very Right wing 18.0%
	Right wing 20.8%
	Moderately Right wing 20.5%
	Center 24.3%
	Moderately Left wing 10.0%
	Left wing 3.61%
	Very Left wing 2.82%
Ideology	
	Right wing 73.2%
	Left wing 26.8%

Table 1.30: Sample Characteristics national Ukraine KIIS survey via telephone N=2,004 (September, 2020)

Age	18-29 15.4% 30-44 26.8% 45-59 28.1% 60+ 29.7%
Gender	Male 47.3%
Education	76.6% completed secondary school and have vocational, or some higher education
Views on Maidan	57.7% supporters of Maidan
Language	Ukrainian 45.1% Russian 47.9% Mix of Ukrainian Russian 7%
Region	West 19.8% Center 38.1% South 28.2% East 7.3% Donbas 6.6%

Table 1.31: Sample Characteristics National Ukraine Survey via telephone $N = 804$ (October 2020)

Age	18-29 11% 30-44 41.4% 45-59 28.5% 60+ 19.2%
Gender	Male 45.2%
Education	93% completed secondary school and have vocational, or some higher education
Views on Maidan	65.3% supporters of Maidan
Language	Ukrainian 45.0% Russian 35.8% Mix of Ukrainian Russian 19.2%
Region	West 25.6% Center 37.8% South 21.8% East 9.3% Donbas 5.5%

Table 1.32: Sample Characteristics National Ukraine Survey via telephone $N = 1,021$ (Septmeber 2021)

Age	18-29 11.9% 30-44 29.1% 45-59 27.5% 60+ 31.5%
Gender	Male 47.0%
Education	94.1% completed secondary school and have vocational, or some higher education
Views on Maidan	61.7% supporters of Maidan
Language	Ukrainian 56.9% Russian 37.3% Mix of Ukrainian Russian 5.8%
Region	West 20.9% Center 38.8% South 26.6% East 8.2% Donbas 5.1%

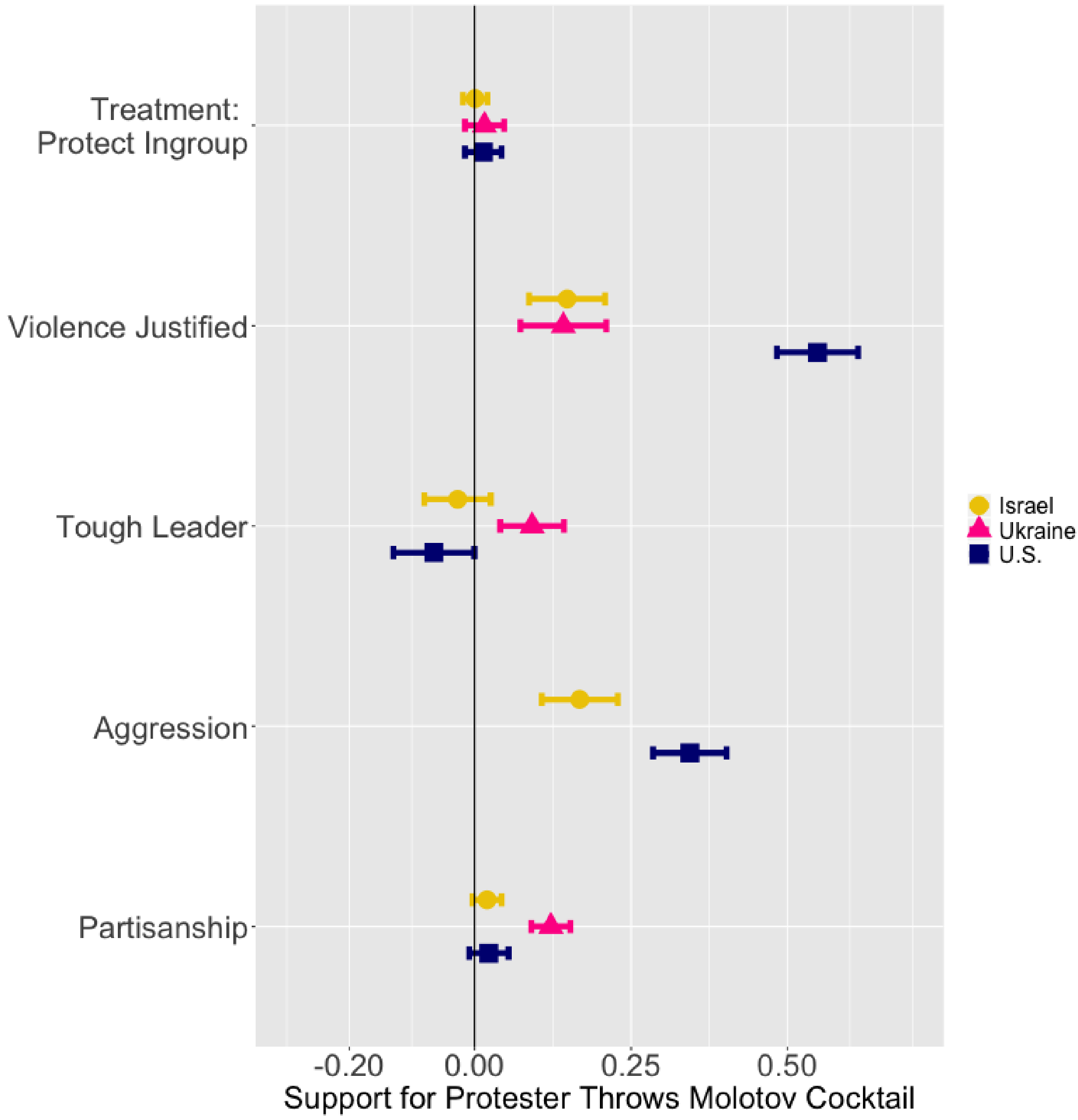
In the U.S. I fielded a follow-up survey in October 2021. 2221 started the survey but 744 didn't pass the same three manipulation checks used previously. A further 11 were dropped for speeding through the survey in less than 2 minutes. Total number of respondents included was 1,467.

Table 1.33: Sample characteristics US LUCID Survey N=1,467 (October 2021)

Age	18-29 19.5% 30-44 29.4% 45-59 25.3% 60 + 25.8%
Partisanship	41.5% Republican
President Approval	Approve of Biden 53.1 %
Gender	48.5% Male
Race	73.4% non-Hispanic White
Education	37.8% Have graduated college or have a graduate degree

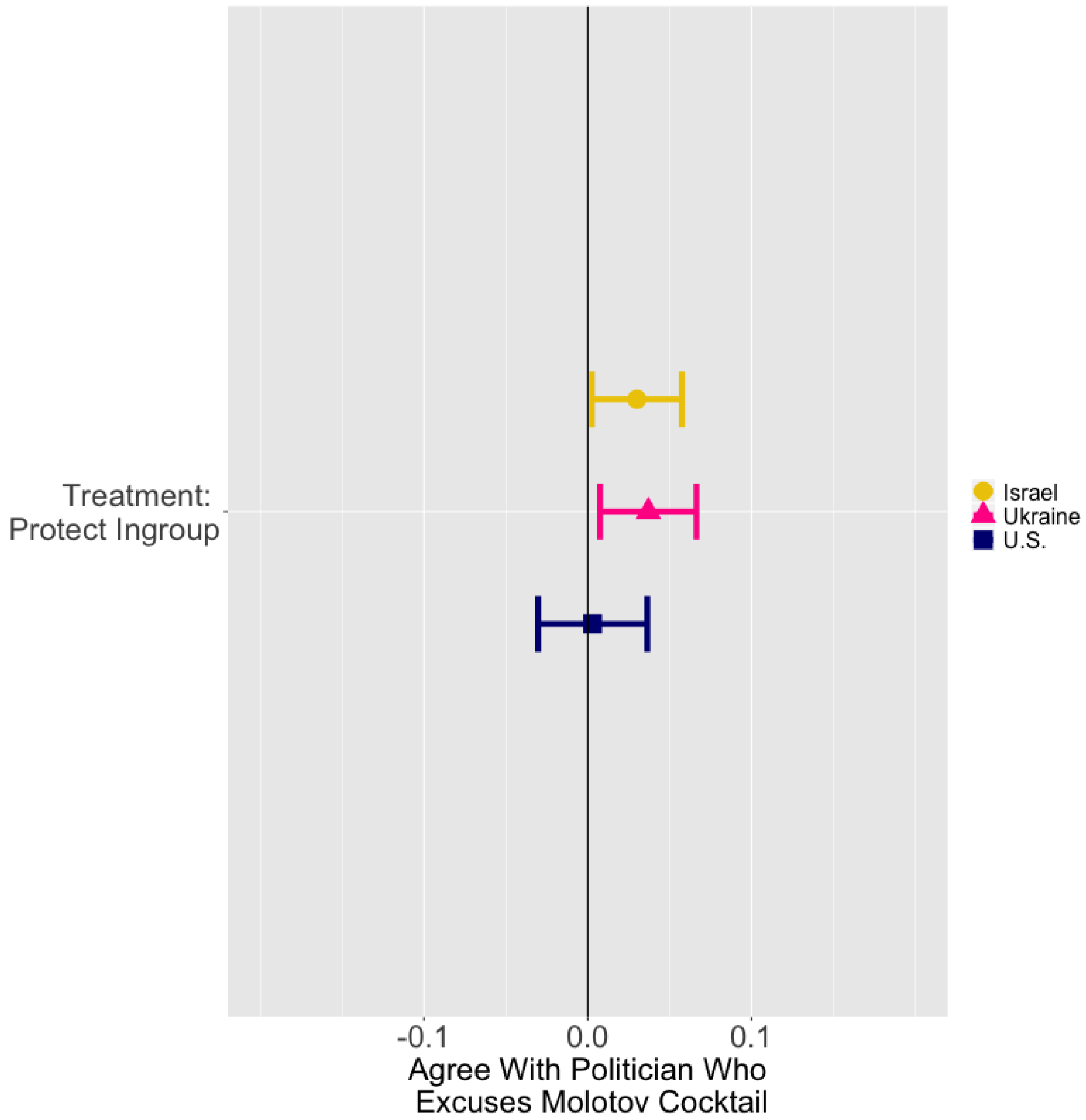
1.7.2 Average Treatment Effects (without controls)

Figure 1.8: Support for a protester who throws a Molotov cocktail at rival political party's headquarters.



Dependent variable is level of support for protester on a 3-point scale rescaled to lie between 0 and 1. 0-disagree with his actions, 0.5-disagree with his actions, but understand why he would do it, 1-agree with his actions. Baseline case for treatment comparison is that the outgroup "deserved it." Surveys were conducted online by iPanel in Israel ($N = 1,342$), via telephone by KIIS/CSI in Ukraine, ($N = 2,004$), and online by LUCID in the U.S. ($N = 1,399$)

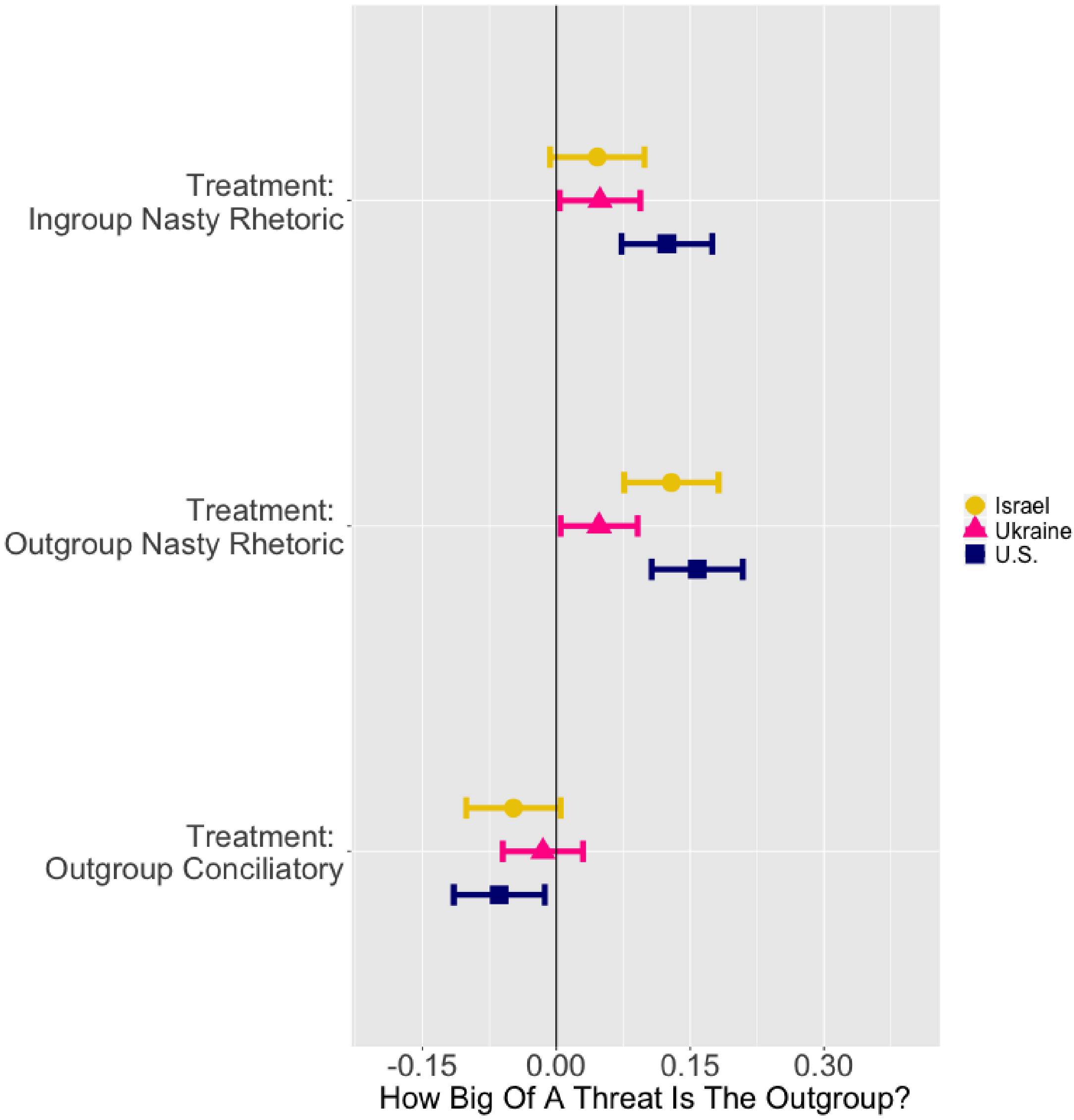
Figure 1.9: Support for a politician who advocates violence (throwing Molotov Cocktail) at rival political party's headquarters.



Dependent variable is level of agreement for a politician who advocated violence on a 5-point scale rescaled to lie between 0 (strongly disagree) and 1 (strongly agree). Baseline case for treatment comparison is that the outgroup "deserved it." Surveys were conducted online by iPanel in Israel ($N = 1,342$), via telephone by KIIS/CSI in Ukraine, ($N = 2,004$), and online by LUCID in the U.S. ($N = 1,399$)

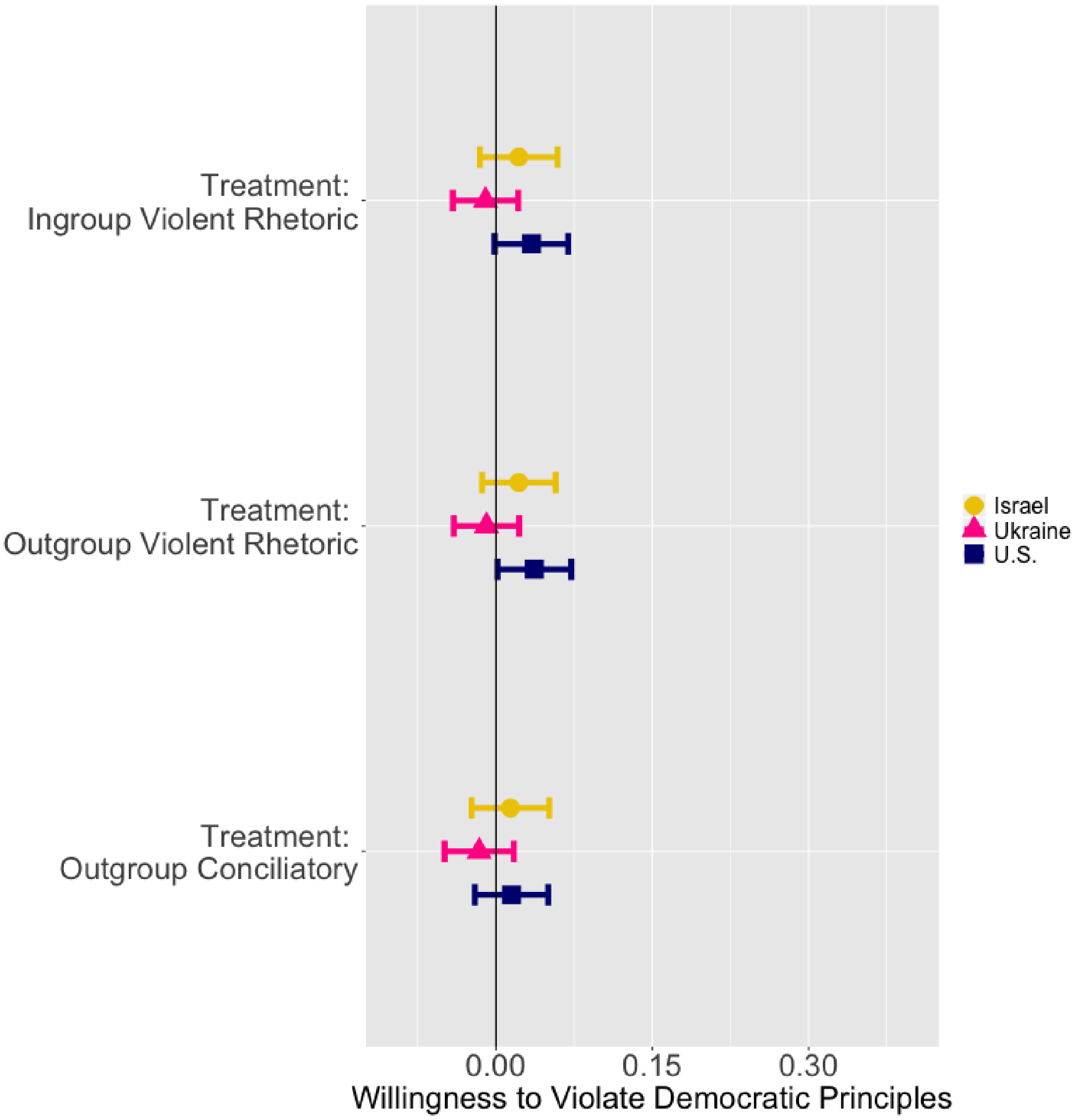
1.7.3 Results for Individual Violations of Democratic Principles

Figure 1.10: How big of a threat is the outgroup?



Dependent variable is how big of a threat is the outgroup on a 5-point scale rescaled to lie between 0 (not a threat at all) and 1 (extreme threat). Baseline case for comparison in ingroup politician makes a conciliatory statement. Surveys were conducted online by iPanel in Israel ($N = 1,342$), via telephone by KIIS/CSI in Ukraine, ($N = 2,004$), and online by LUCID in the U.S. ($N = 1,399$)

Figure 1.11: Willingness to Subvert Democrat Principles



Dependent variable is an additive index of willingness to 1) ban certain outgroup politicians from social media, 2) dispute elections where outgroup wins, 3) ban certain outgroup politicians from the outgroup, 4) make it illegal for radical outgroups to protest rescaled to lie between 0 (strongly disagree with all of these) and 1 (strongly agree with all of them). Baseline case for comparison in ingroup politician makes a conciliatory statement. Surveys were conducted online by iPanel in Israel ($N = 1,342$), via telephone by KIIS/CSI in Ukraine, ($N = 2,004$), and online by LUCID in the U.S. ($N = 1,399$)

Table 1.34: Individual Items Support for Violating Democratic Principles (Israel Individual Items)

	Dependent variable:							
	Ban Outgroup Politicians' Social Media		Wouldn't Accept Elections if Outgroup Won		Ban Certain Outgroup Politicians		Ban Protests By Outgroup	
Treat: Ingroup Violent Rhetoric	0.033	0.027	0.021	0.013	0.020	0.016	0.013	0.006
	(0.024)	(0.024)	(0.020)	(0.020)	(0.026)	(0.026)	(0.028)	(0.028)
Treat: Outgroup Violent Rhetoric	0.031	0.027	0.038*	0.032*	0.027	0.023	-0.006	-0.010
	(0.024)	(0.024)	(0.020)	(0.019)	(0.026)	(0.026)	(0.027)	(0.027)
Treat: Outgroup Conciliatory	0.023	0.021	0.015	0.011	0.004	0.003	0.013	0.011
	(0.024)	(0.024)	(0.020)	(0.020)	(0.026)	(0.026)	(0.028)	(0.028)
Violence Justified		0.186***		0.230***		0.166***		0.186***
		(0.053)		(0.043)		(0.057)		(0.061)
Tough Leader		0.057		-0.001		0.095*		0.069
		(0.045)		(0.036)		(0.048)		(0.051)
Aggression		0.181***		0.052		0.082		0.114*
		(0.052)		(0.042)		(0.056)		(0.060)
Right Wing Supporter		-0.002		0.031*		-0.056***		0.060***
		(0.019)		(0.016)		(0.021)		(0.022)
Constant	0.300***	0.238***	0.155***	0.110***	0.311***	0.292***	0.367***	0.266***
	(0.017)	(0.028)	(0.014)	(0.023)	(0.018)	(0.030)	(0.019)	(0.032)
Observations	1,060	1,060	1,060	1,060	1,060	1,060	1,060	1,060
R^2	0.002	0.033	0.004	0.040	0.001	0.023	0.001	0.027
Adjusted R^2	-0.001	0.026	0.001	0.033	-0.001	0.017	-0.002	0.021

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 1.35: Support for Violating Democratic Principles (Ukraine Individual Items)

	Dependent variable:							
	Ban Outgroup Politicians' Social Media		Wouldn't Accept Elections if Outgroup Won		Ban Certain Outgroup Politicians		Ban Protests By Outgroup	
Treat: Ingroup Violent Rhetoric	-0.024	-0.021	0.005	0.014	-0.0003	0.0003	-0.028	-0.028
	(0.022)	(0.022)	(0.019)	(0.020)	(0.022)	(0.023)	(0.022)	(0.023)
Treat: Outgroup Violent Rhetoric	-0.019	-0.013	-0.008	-0.009	-0.012	-0.019	-0.005	0.006
	(0.021)	(0.022)	(0.019)	(0.020)	(0.021)	(0.022)	(0.022)	(0.022)
Treat: Outgroup Conciliatory	0.001	0.006	-0.003	0.005	-0.009	-0.013	-0.034	-0.024
	(0.022)	(0.023)	(0.020)	(0.020)	(0.022)	(0.023)	(0.022)	(0.023)
Violence Justified		0.074^{**}		0.078^{**}		0.097^{***}		-0.075^{**}
		(0.035)		(0.032)		(0.036)		(0.036)
Tough Leader		0.032		0.017		-0.008		0.030
		(0.027)		(0.024)		(0.027)		(0.027)
Pro-Maidan		0.055^{***}		0.043^{***}		0.090^{***}		-0.061^{***}
		(0.016)		(0.015)		(0.016)		(0.016)
Constant	0.408^{***}	0.350^{***}	0.350^{***}	0.301^{***}	0.430^{***}	0.369^{***}	0.470^{***}	0.498^{***}
	(0.015)	(0.023)	(0.014)	(0.020)	(0.015)	(0.022)	(0.015)	(0.023)
Observations	1,622	1,501	1,584	1,467	1,618	1,488	1,619	1,489
R^2	0.001	0.012	0.0003	0.011	0.0003	0.026	0.002	0.016
Adjusted R^2	-0.001	0.009	-0.002	0.007	-0.002	0.022	0.0004	0.012

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1.36: Support for Violating Democratic Principles (U.S. Individual Items)

	Dependent variable:							
	Ban Outgroup Politicians' Social Media		Wouldn't Accept Elections if Outgroup Won		Ban Certain Outgroup Politicians		Ban Protests By Outgroup	
Treat: Ingroup Violent Rhetoric	0.033	0.031	0.065***	0.066***	0.032	0.031	0.004	0.003
	(0.023)	(0.022)	(0.023)	(0.022)	(0.023)	(0.021)	(0.022)	(0.021)
Treat: Outgroup Violent Rhetoric	0.038	0.030	0.055**	0.052**	0.037	0.032	0.018	0.015
	(0.024)	(0.022)	(0.024)	(0.022)	(0.023)	(0.021)	(0.022)	(0.021)
Treat: Outgroup Conciliatory	0.010	-0.006	0.029	0.016	0.009	-0.005	0.009	-0.001
	(0.023)	(0.022)	(0.023)	(0.022)	(0.023)	(0.021)	(0.022)	(0.021)
Violence Justified		0.253***		0.300***		0.258***		0.204***
		(0.034)		(0.034)		(0.033)		(0.033)
Tough Leader		-0.096***		-0.048		-0.064*		-0.066**
		(0.034)		(0.034)		(0.033)		(0.033)
Aggression		0.206***		0.153***		0.172***		0.142***
		(0.031)		(0.031)		(0.031)		(0.031)
Republican		-0.031*		0.012		0.005		0.035**
		(0.016)		(0.016)		(0.016)		(0.016)
Constant	0.436***	0.378***	0.436***	0.345***	0.469***	0.391***	0.499***	0.427***
	(0.016)	(0.021)	(0.016)	(0.021)	(0.016)	(0.021)	(0.015)	(0.021)
Observations	1,398	1,398	1,398	1,398	1,398	1,398	1,398	1,398
R^2	0.002	0.155	0.007	0.153	0.003	0.141	0.001	0.102
Adjusted R^2	0.0003	0.151	0.005	0.149	0.0004	0.136	-0.002	0.097

Note: *p<0.1; **p<0.05; ***p<0.01

Chapter 2

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