Online Appendix

Transcript text analysis – supplemental figures and tables

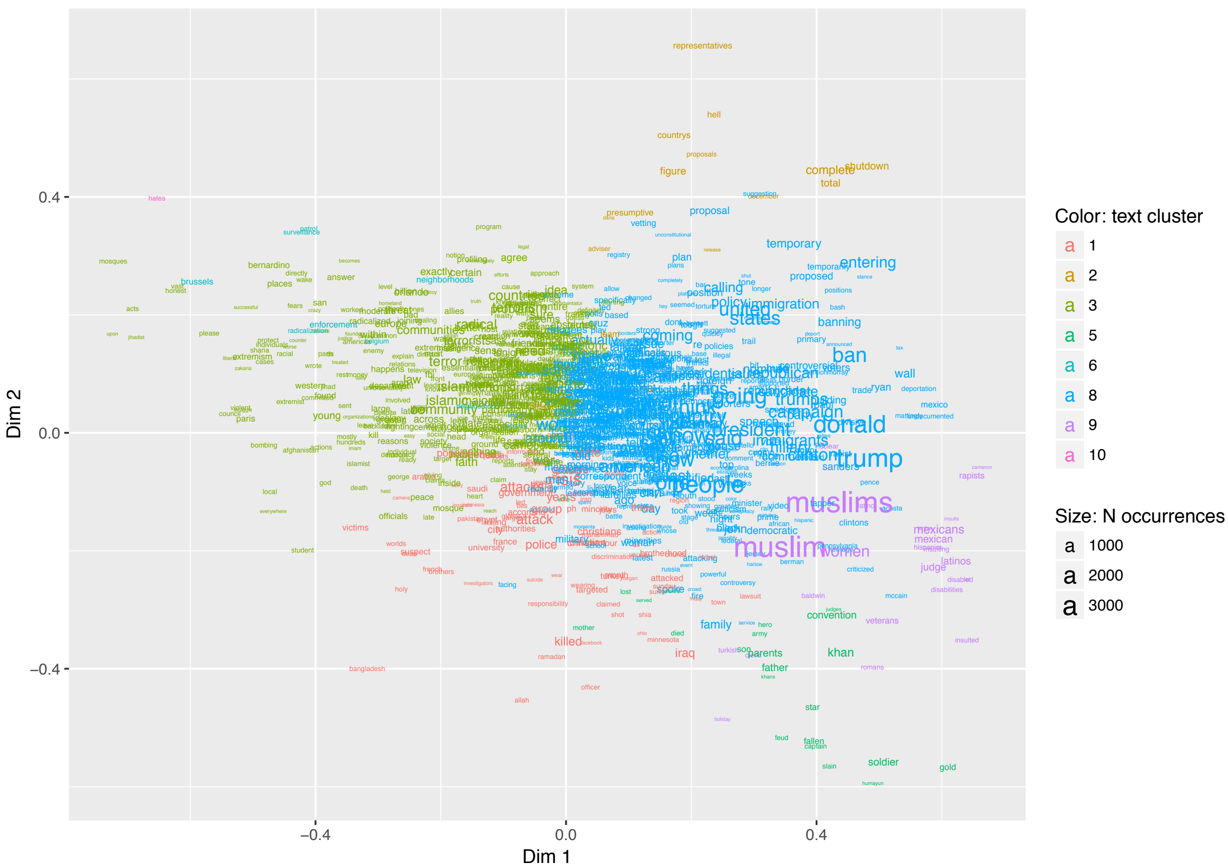

Figure A1: *Word co-occurrence view of word clusters - top 2 dimensions.* Colors are from posthoc k means clustering that used 10 clusters on the top 10 dimensions of the output. These colors are used only to make the figure somewhat easier to read and are not used in the analyses. The ‘specific’ keywords in the Table A1 are based on the numeric values on the x and y axes of this output multiplied by the weight of the words in the overall scaling output.

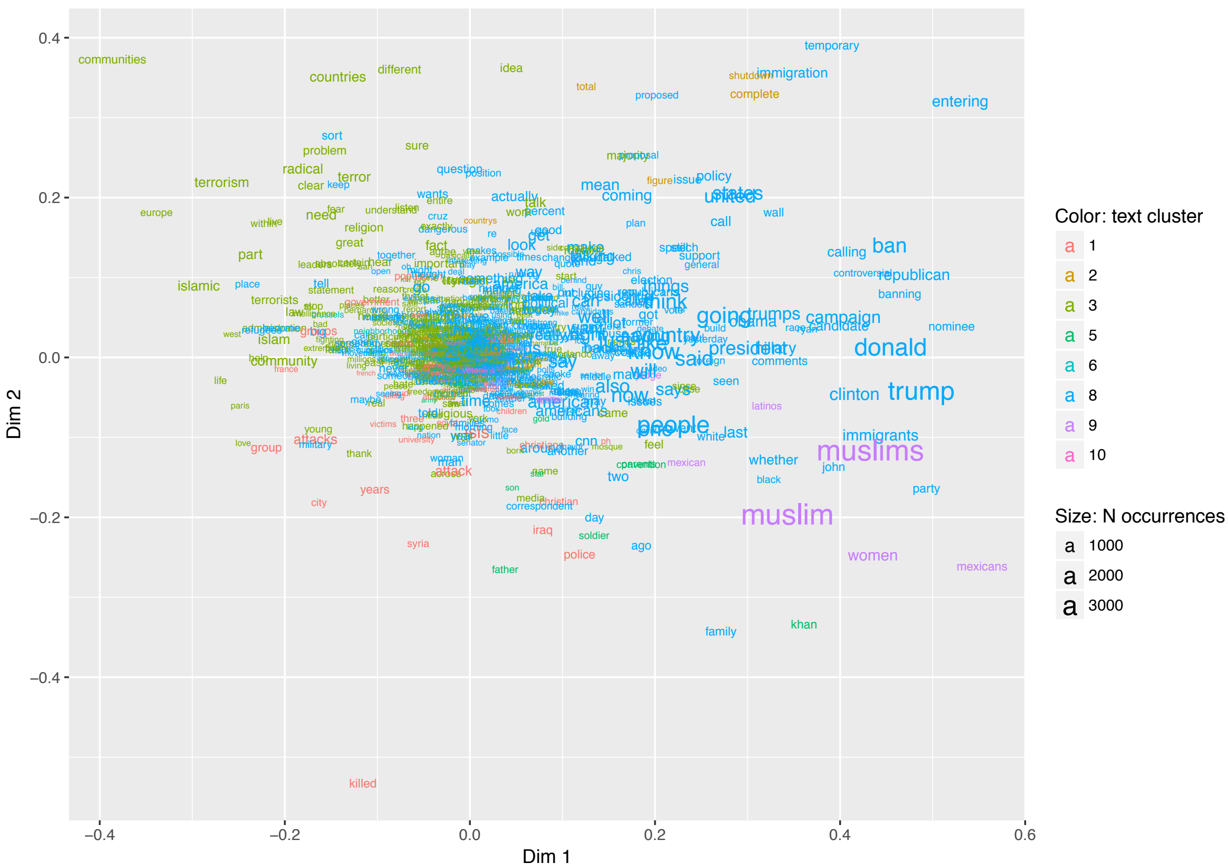

Figure A2: *Word count view of word clusters - top 2 dimensions.* Colors are from posthoc k means clustering that used 10 clusters on the top 10 dimensions of the output. These colors are used only to make the figure somewhat easier to read and are not used in the analyses. The ‘common’ keywords in the Table A2 are based on the numeric values on the x and y axes of this output multiplied by the weight of the words in the overall scaling output.

Specific keywords appearing with mention of “Muslim(s)” in news coverage

Dimension 1		Dimension 2		Dimension 3		Dimension 4		Dimension 5	
mexicans	brussels	temporary	soldier	khan	mexicans	communities	shutdown	police	mexicans
wall	mosques	immigration	khan	convention	muslims	need	complete	cruz	women
latinos	paris	countries	iraq	soldier	isis	problem	total	ted	latinos
trump	young	different	gold	fallen	muslim	work	countrys	neighborhoods	sayyid
entering	bernardino	entering	killed	parents	latinos	let	entering	enforcement	adultery
donald	san	communities	family	nominee	people	soldier	hell	terror	tyrannies
ban	law	idea	father	son	turkey	lot	figure	state	jails
women	within	shutdown	star	constitution	syria	community	representatives	surveillance	piro
muslims	europe	complete	parents	captain	women	mean	calling	belgium	mater
judge	extremism	total	fallen	father	brotherhood	feel	saudi	intelligence	backward
mexican	places	problem	convention	democratic	christians	cruz	male	correspondent	eloping
khan	victims	proposed	son	speaker	police	son	arabia	patrol	vietnamese
shutdown	violent	sort	captain	presumptive	group	heard	unidentified	plan	seducing
banning	enforcement	radical	women	sacrifice	christian	fallen	sayyid	security	offenders
ryan	acts	policy	muslim	paul	rapists	father	london	former	martyrs

Table A1

Common keywords appearing with mention of “Muslim(s)” in news coverage

Dimension 1		Dimension 2		Dimension 3		Dimension 4		Dimension 5	
entering	islamic	temporary	killed	khan	muslims	lot	entering	police	women
trump	communities	immigration	family	nominee	isis	law	shutdown	security	come
republican	terrorism	entering	khan	great	muslim	let	complete	terror	election
mexicans	part	countries	women	tonight	mexicans	communities	total	state	really
donald	islam	different	police	family	people	security	calling	call	every
ban	community	idea	mexicans	calling	women	community	election	paul	mexicans
muslims	group	communities	muslim	election	immigrants	fact	group	cnn	actually
women	europe	shutdown	iraq	house	going	point	temporary	law	immigrants
immigrants	terrorists	complete	day	democratic	community	mean	state	attacks	let
nominee	radical	problem	syria	show	attack	today	states	banning	man
party	law	total	party	cnn	group	work	million	terrorist	things
clinton	place	radical	father	trumps	white	family	number	killed	religion
campaign	attacks	policy	two	republican	think	kind	united	correspondent	never
banning	need	mean	attack	presidential	unidentified	fight	figure	isis	male
candidate	problem	terrorism	years	paul	million	feel	unidentified	course	american

Table A2

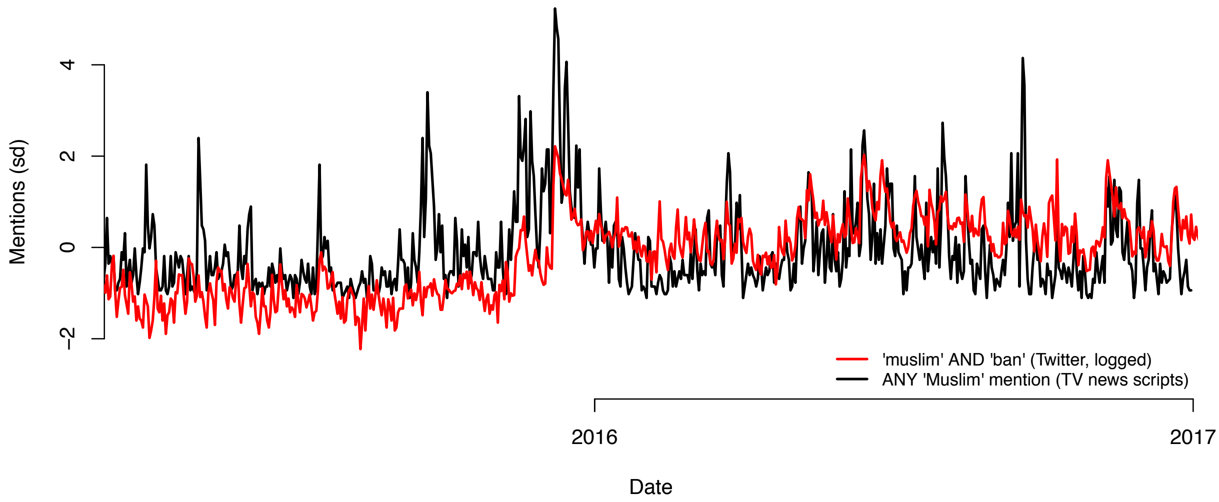

Figure A3: *Comparison of Television News Coverage of Muslims and Twitter mentions of a Muslim ban.* In black, the number of mentions of 'Muslim' in the TV news scripts in standard deviation units; in red, the logged number of mentions of 'Muslim' and 'ban' on Twitter in standard deviation units.

Twitter geotagging – voter record replication and control group comparisons

In addition to the analysis of all geotags from Twitter users in the United States with Arabic sounding names, we also analyze a subset of these users who appear in a data set linked to voter records, as well as a demographically matched control group.

The linked data set was created by a group of researchers affiliated with one of the authors. The voter records were provided by a commercial vendor and include basic demographic information including age, gender, and race. The Twitter-linked data set construction followed these steps:

- Create list of Twitter user IDs appearing in a 10% sample of all of tweets (Twitter "Decahose") between January 2014 and June 2015
- Parse Twitter profile for name and U.S. state
- Keep Twitter user IDs with first name and last name that were unique in a state in the Twitter sample and unique by city and/or state in the voter record

We created a replication sample of Arabic sounding name users by referencing first name in the voter record data set against the same distinctively Arabic name data used in our main analyses.

Table A3 shows the demographic comparisons of the geotagging vs. general Twitter sample for voters with Arabic sounding names. We observe no large demographic differences for the two groups. This suggests that, in our Arabic name samples, people sharing location in a user profile (e.g. "I'm from Texas.") are demographically similar to those geotagging precise coordinates.

For the matched control groups, we sampled 50,000 users with similar demographics to the Twitter users with Arabic sounding names in the voter records. 50,000 demographically matched Twitter users produced a similar number of geotagging users compared to our Arabic name sample. The control group was matched on state, gender, age group, and party affiliation. Age groups were in 5 year increments (e.g. (1985 to 1990)).

Specifically, we calculated the number of Arabic sounding name and total Twitter users for each combination of state, gender, age group, party affiliation. We sampled individuals proportional to the ratio of Arabic sounding users to total users in each combination, removing the Arabic sounding users from the sampling stage. This over-sampled individuals with similar demographics to the distinctively Arabic named users. In the analyses, we then weighted individuals following Iacus et al. (2011) according to the same ratios recalculated within the smaller sample. These users are not matched exactly in the analyses, however, because there were small differences in who geotags (and we sampled based on having a Twitter account).

This control group appeared to sample users with unusual names because the Arabic sounding name sample was concentrated in states with large populations, increasing the likelihood of multiple first and last name matches. This potentially over-sampled religious, ethnic, and racial minorities who might also respond negatively to the campaign rhetoric.

Table A3: *Descriptive statistics for Arabic sounding name voter sample.* Percentages do not add to 100 where data is missing for gender and other category for party affiliation and race/ethnicity. These variables were not available in all states. The Arabic name sample was more male than female due to the name dictionary. Where we have detailed ethnicity information, we do not observe significantly more Middle Eastern men than women on Twitter.

	Arabic sounding name voters geotagging on Twitter 11/2015 or 12/2015 (unique name in state)	**Arabic sounding name voters on Twitter** (unique name in state)
Age		
Mean	33	34
SD	9	13
Gender		
Male	74%	72%
Female	26%	26%
Party Affiliation		
Democrat	32%	37%
Republican	6%	5%
Top 4 States		
California	21%	16%
New York	18%	11%
Texas	13%	9%
Florida	6%	7%
Race/ethnicity (not matched)		
White/Caucasian	35%	32%
Black/African-American	17%	21%
N	147	4043

Because of this, we compare this control group to both our original Arabic name sample, as well as a more precise Arabic name sample who used posted Arabic language tweets at some point over our observation period. Including Arabic speakers reduces the likelihood of an incorrect match to someone who is not Muslim. This matters because our Arabic named sample likely includes many people who are not Muslim and our control sample potentially includes many other religious and ethnic minorities. This is an additional test where we might expect a larger (or better measured) effect.

We show the results for both the Arabic name and Arabic name plus Arabic language sample in Figure A4. For the Arabic name plus language sample, drops on both Instagram and other platforms are visibly larger than the control group. For the somewhat larger control group in the figure, the counts are the sums of the users' weights multiplied by the ratios of the two group means (Arabic over control) before December 2nd, so that the lines can be seen at the same level before the drop.

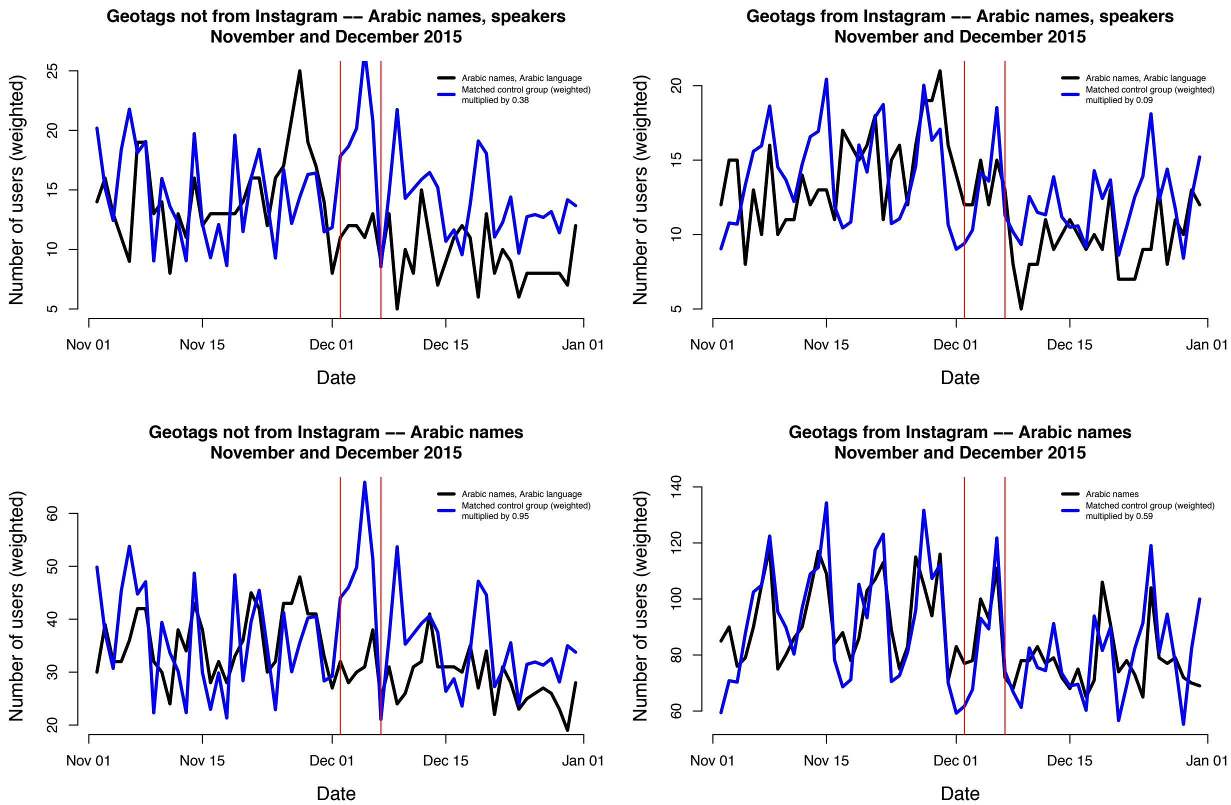

Figure A4: *Drops in Arabic name, Arabic name and language, and Arabic name voter samples compared to a matched control group by source of tweet.*

We evaluate the significance of these differences in the Poisson regression table below (Table A4). We add the under-powered voter sample replication to this table as well. This test uses all geotagged data because there was insufficient data to analyze other platforms separately from Instagram. The data in the regressions is not multiplied by the ratio of the means because the models measure relative changes rather than absolute ones.

These tests pick up some declines among the control group, but these changes are smaller than for the Arabic samples.

In Table A4, the results do not account for some users appearing on more dates than others. In Table A5, we show quasi-Poisson regressions predicting whether a user was less likely to geotag at all after December 2nd. These regressions are nearly equivalent to logistic regressions, but the coefficients are more interpretable and can be interpreted as risk ratios (e.g. 10% less likely to post). Each individual in this analysis is counted twice: once before December 2nd and once after.

Table A4: *Change in geotagging in Arabic samples compared to control group – aggregate.* The dependent variable is the number of people geolocating on a given day.

	Dependent variable:				
	Number of users geotagging on a given day				
	Arabic name, language Not Instagram	Arabic name, language Instagram	Arabic name Not Instagram	Arabic name Instagram	Arabic name, voter All geotags
Arabic	−0.98 p < 0.01	−2.39 p < 0.01	−0.07 p = 0.08	−0.52 p < 0.01	−2.73 p < 0.01
Date >"2015-12-02"	−0.01 p = 0.90	−0.15 p < 0.01	−0.01 p = 0.90	−0.15 p < 0.01	−0.12 p < 0.01
Arabic:Date >"2015-12-02"	−0.40 p < 0.01	−0.21 p = 0.01	−0.22 p < 0.01	−0.02 p = 0.54	−0.13 p = 0.10
Constant	3.66 p < 0.01	5.06 p < 0.01	3.66 p < 0.01	5.06 p < 0.01	5.27 p < 0.01
Observations	122	122	122	122	122

Table A5: *Change in geotagging in Arabic samples compared to control group – individual level.* The dependent variable is whether an individual precisely geolocated at all.

	Dependent variable:				
	One or more geotags				
	Arabic name, language Not Instagram	Arabic name, language Instagram	Arabic name Not Instagram	Arabic name Instagram	Arabic name, voter All geotags
Arabic	0.08 p = 0.37	0.02 p = 0.70	0.05 p = 0.42	−0.02 p = 0.39	0.01 p = 0.86
Date >"2015-12-02"	0.001 p = 0.99	−0.20 p < 0.01	0.001 p = 0.99	−0.20 p < 0.01	−0.17 p < 0.01
Arabic:Date >"2015-12-02"	−0.12 p = 0.34	−0.16 p = 0.08	−0.13 p = 0.11	−0.01 p = 0.85	−0.15 p = 0.14
Constant	−0.32 p < 0.01	−0.25 p < 0.01	−0.32 p < 0.01	−0.25 p < 0.01	−0.24 p < 0.01
Observations	546	2,652	946	4,664	2,790

Table A5 shows that more active users contributed to the drop in geotags on platforms other than Instagram among Arabic named users who used Arabic on Twitter, but that the other results were not heavily driven by a small number of people. The coefficient for column one of the table is near the coefficient in the previous table only after modeling the number of days active.

Twitter geotagging – supplemental figures and tables

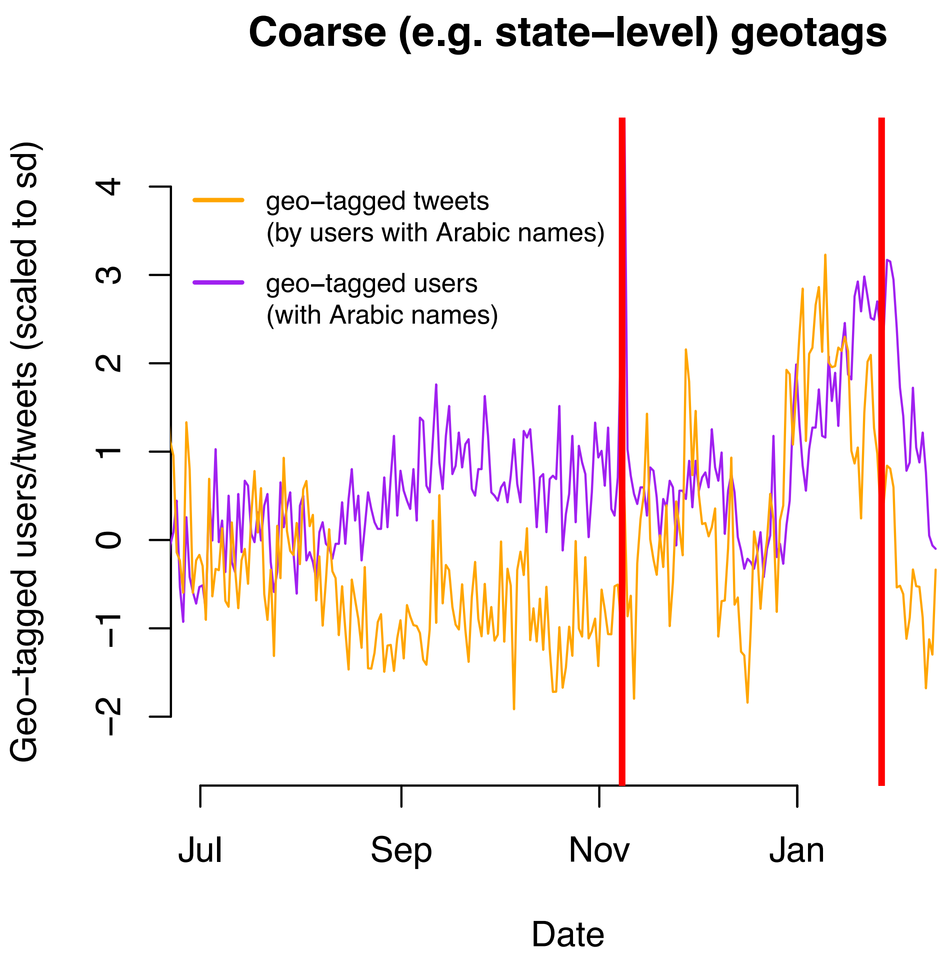

Figure A5: *Other geotagged tweets (i.e. state-level geotags) by Arabic named Twitter users.* The red lines are 1) the 2016 election 2) the executive order.

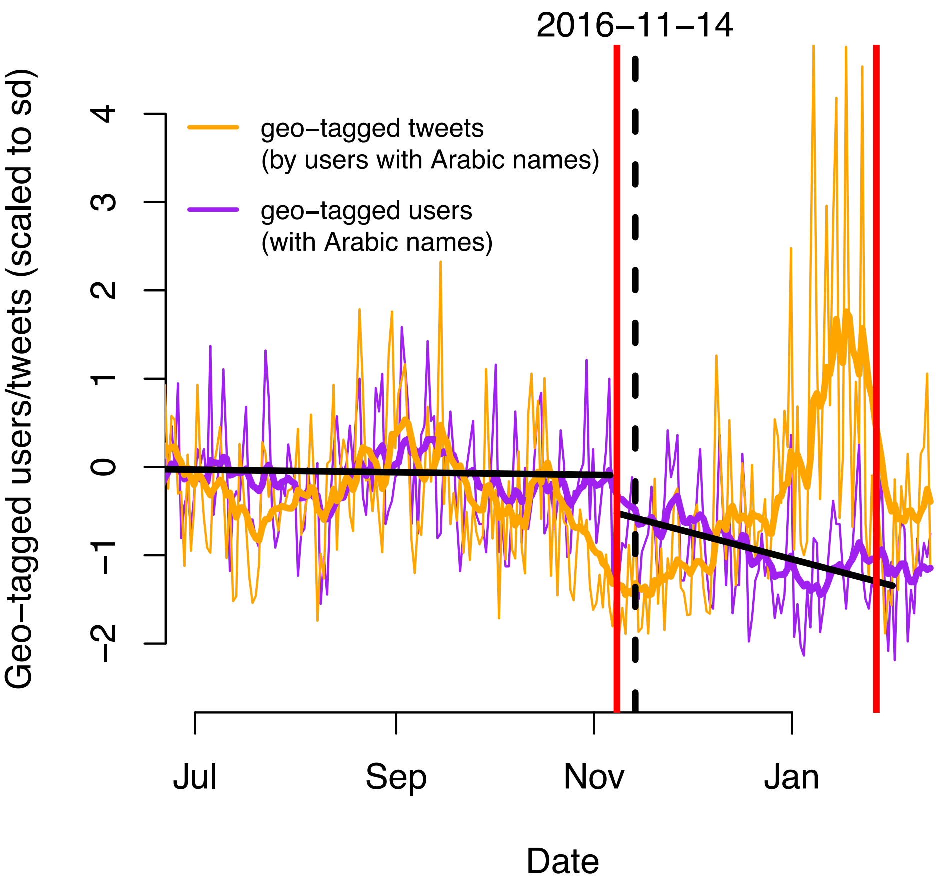

Figure A6: Vertical black dotted lines identified using the method described in Bai and Perron (2003) with the number of breaks set to two. The red lines are 1) the 2016 election 2) the executive order.

Common keywords appearing in the precisely geotagged tweets between November 7, 2016 and January 27, 2017							
Dimension 2		Dimension 3		Dimension 4		Dimension 5	
posted	one	today	new	just	ca	back	got
just	time	just	york	posted	san	los	york
photo	day	can	ny	photo	francisco	miami	photo
ca	great	see	square	houston	angeles	beach	city
international	going	california	city	happy	los	thank	just
san	year	now	back	love	airport	angeles	new
los	know	day	amazing	texas	international	happy	posted
francisco	work	christmas	boston	tx	city	get	san
airport	last	like	place	house	california	amp	one
california	today	house	nyc	new	great	ca	much
video	best	know	school	florida	us	place	last
angeles	get	birthday	brooklyn	dallas	thanks	take	will
park	night	world	miami	art	night	airport	show
florida	thank	us	year	university	last	birthday	never
beach	friends	houston	take	good	come	international	francisco

Table A6: This table shows the keywords for top dimensions of the precisely geolocated tweets in our Arabic name sample between November 7, 2016 and January 27, 2017. Most keywords are related locations, including cities and destinations like parks, beaches and airports. These tweets were not obviously political. Note that this time frame selects people who did not hide their location. The method uses a version of (Hobbs 2016) adjusted for Twitter data to handle more repetitive and noisy language than seen in open-ended surveys. This version takes the square root of co-occurrences before scaling and requires that all words' scores sum to approximately the same size. The first dimension captures word frequency and document length. 1 out of 5 tweets were sampled inversely proportional to how often an individual tweeted so that highly active individuals were not counted much more than less active people.

Common keywords appearing in the coarsely (e.g. state-level) geotagged tweets between November 7, 2016 and January 27, 2017							
Dimension 2		Dimension 3		Dimension 4		Dimension 5	
like	happy	day	just	love	night	happy	get
never	man	sad	home	will	know	birthday	go
people	birthday	amp	look	best	now	great	want
love	good	lol	come	one	fuck	love	take
say	bro	thank	back	amp	last	sure	right
even	year	love	game	new	real	make	going
know	best	really	get	home	years	much	everyone
much	time	thanks	time	bro	hope	tonight	stop
can	ever	still	always	still	right	lmao	year
hate	great	see	got	hate	shit	us	back
us	back	realdonaldtrump	someone	got	good	true	good
shit	big	good	think	go	really	hope	school
please	thanks	god	right	wait	even	money	trump
still	miss	happy	new	ever	true	know	keep
want	new	please	say	school	great	game	old

Table A7: This table shows the keywords for top dimensions of the coarsely (e.g. state-level) geolocated tweets in our Arabic name sample between November 7, 2016 and January 27, 2017. Most keywords are not associated with a location (we do not analyze these tweets in our main analyses). There were both more users and more tweets for this sample after the 2016 election. Unlike the precisely geotagged tweets (the focus of this article), these tweets without specific location information contained some political keywords – mentions of Donald Trump. Note that this time frame selects people who did not hide their state-level location. The method uses a version of (Hobbs 2016) adjusted for Twitter data to handle more repetitive and noisy language than seen in open-ended surveys. This version takes the square root of co-occurrences before scaling and requires that all words' scores sum to approximately the same size. The first dimension captures word frequency and document length. 1 out of 100 tweets were sampled inversely proportional to how often an individual tweeted so that highly active individuals were not counted much more than less active people.

Survey – Changes in the trends of surveying Muslim Americans in 2016

One of the takeaways from the results presenting changes in geocoded Twitter accounts is that accounts with Arab names had become less visible around the major political events of the 2016 election year. We substantiate this result in the voter record as well, with the caveat that after the election, the drops may be limited to non-citizens only.

Here, we provide evidence that it also became increasingly difficult to survey Muslim American respondents throughout the 2016 election year. Between June 2016 - February 2017, we contracted with Survey Sampling International (SSI) to survey Muslim Americans on three occasions.

Table A8: Descriptives on Surveying Muslim Americans in Three Data Collection Efforts

Dataset	**Number of individuals sent to the Qualtrics survey**	**Number of Muslims SSI sent to the survey who consented to the survey and identified as Muslim**	**Number of Muslim respondents who finished the full survey**
June 2016	280	–	204
December 2016	289	169	149
February 2017	1062	–	204

Our first data collection effort was in June 2016, one month before the Republican National Convention. We contracted with Survey Sampling International (SSI) for a convenience sample of 200 Muslim American respondents. SSI sent 280 respondents to our survey. Of those who began the survey, 204 completed the full questionnaire.

Next and in December 2016, one month after the November 2016 election, we once again contracted with SSI to sample another 200 Muslim American respondents. When we began to explore the results in January 2017, we found some inconsistencies in the survey responses. On February 13, 2017, SSI conducted a fraud investigation on the December 2016 dataset and found that 24.2% of the 289 sample sent to the survey was not Muslim (70 respondents). After removing these individuals, 169 observations in the dataset identified as Muslim and consented to the survey. Of the 169 respondents who were Muslim, 149 completed the survey. SSI agreed to field a third survey for us to correct for the 70 non-Muslim responses.

The third survey was launched on February 24, 2017. The results presented in this paper come from this third survey. In this survey, individuals were prompted to answer a series of demographic questions, including identifying their religion. If they selected "Islam," they were allowed to continue with the survey. If not, they were excluded from the survey. In sum, SSI sent 1,062 potential Muslim American respondents to Qualtrics survey, yet only 230 selected Islam as their religion. It remains unknown whether this was because individuals were afraid of selecting "Islam" as their religion, whether this was because non-Muslims have been impersonating Muslims on online surveys or whether there is another reason remains unknown. When all was said and done, SSI recruited 208 completes in 10 days.

As Table A9 indicates, over 750 potential Muslim respondents were sent to the survey in two days (between February 28, 2017 and March 1, 2017). While we cannot know for certain, it appears that identifying Muslim respondents who were willing to take the survey proved increasingly more difficult, despite the target number of respondents being very small. Overall, we present this information as additional evidence demonstrating that reaching Muslim Americans during the 2016 election year and in its aftermath proved progressively more difficult.

Table A9: Recruitment Efforts by Date for the Third Survey

Date	**Number of individuals sent to the Qualtrics survey**
2/24/17	31
2/25/17	38
2/26/17	36
2/27/17	37
2/28/17	552
3/1/17	205
3/2/17	82
3/3/17	59
3/4/17	21
3/5/17	1

As researchers trying to survey Muslim Americans, using the same survey company that many other scholars rely on, our anecdotal experience proved that reaching the group as research subjects became more difficult.

Survey – Explanation of Variables and Descriptive Table

Respondents were asked to answer a question on their religiosity on a 5 point scale. The question was: "How often do you attend religious services at the mosque or masjid?" Possible answers were: (1) Never, (2) Only on religious holidays, (3) Once a month, (4) Once a week, and (5) More than once a week. From here, we created a "religious" variable where a value of 1 indicated that the individual respondent attended religious services 'once a week' or 'more than once a week' and 0 if the subject attended the mosque or masjid 'never,' 'only on religious holidays' or 'once a month.' In sum, 101 respondents (48.56%) fell into the high religious category and 107 respondents (51.54%) into the low religious category. Our linked fate question asks "Do you think that what happens to Muslims in this country will affect what happens to your life?" Of the 208 respondents in our sample, 115 answered 'Yes, a lot' and 67 answered 'Yes, a little' and 26 answered 'No.' We coded those who responded with 'Yes, a lot' as having high linked fate and those who responded 'Yes, a little' or 'No' as having low linked fate.

Respondents were also asked to rate their behavioral shifts over the last 12 months: "[t]o what extent have you changed your behavior in the following ways?" They were asked to evaluate the following statements on a 4-point Likert scale (1= *Never*, 2 = *Once in a while*, 3 = *Somewhat often*, and 4 = *Very often*): (1) Avoided interactions with members of another social group, (2) Avoided interactions with members of another political party, (3) Limited posts on social media, and (4) Less frequently visited restaurants, shopping malls, parks or other public places. On average, respondents rated these avoidance statements as 2 or higher, indicating that they reported having had segregated or censored themselves at least somewhat often or very often over the last 12 months (see Table A10).

Across the board, we observe significant differences in means between those with low religiosity and those with high religiosity for each of the avoidance statements examined. In other words, those who attended the mosque about once a week or more than once a week were significantly more likely to reduce their visibility and visit public spaces less often. We find similar results for those with high linked fate and those with low linked fate; except for with respect to avoidance statement 1, which measures avoiding interactions with members of another social group. In this instance, the difference is in the same direction as with the other avoidance behaviors, but is not statistically significant.

Table A10: Descriptive Statistics for avoidance statements

	Mean	SD	Min	Max	N
Low Religiosity					
Avoidance Statement 1	1.803738	1.041038	1	4	107
Avoidance Statement 2	1.88785	.9936316	1	4	107
Avoidance Statement 3	1.897196	1.106879	1	4	107
Avoidance Statement 4	1.747664	1.000881	1	4	107
High Religiosity					
Avoidance Statement 1	2.326733	1.105522	1	4	101
Avoidance Statement 2	2.534653	1.212966	1	4	101
Avoidance Statement 3	2.514851	1.162875	1	4	101
Avoidance Statement 4	2.376238	1.1563	1	4	101
Low Linked Fate					
Avoidance Statement 1	1.956989	1.122051	1	4	93
Avoidance Statement 2	1.967742	1.117563	1	4	93
Avoidance Statement 3	1.903226	1.142694	1	4	93
Avoidance Statement 4	1.817204	1.031527	1	4	93
High Linked Fate					
Avoidance Statement 1	2.13913	1.083261	1	4	115
Avoidance Statement 2	2.391304	1.144749	1	4	115
Avoidance Statement 3	2.434783	1.148076	1	4	115
Avoidance Statement 4	2.243478	1.159184	1	4	115
Full Sample					
Avoidance Statement 1	2.057692	1.101838	1	4	208
Avoidance Statement 2	2.201923	1.149499	1	4	208
Avoidance Statement 3	2.197115	1.173208	1	4	208
Avoidance Statement 4	2.052885	1.121632	1	4	208

Avoidance Statement 1: “Avoided interactions with members of another social group”

Avoidance Statement 2: “Avoided interactions with members of another political party”

Avoidance Statement 3: “Limited posts on social media”

Avoidance Statement 4: “Less frequently visited restaurants, shopping malls, parks, or other public places”

Responses measured on a Likert scale: 1 = never, 2 = once in awhile, 3 = somewhat often, 4 = very often

Survey – supplemental figure

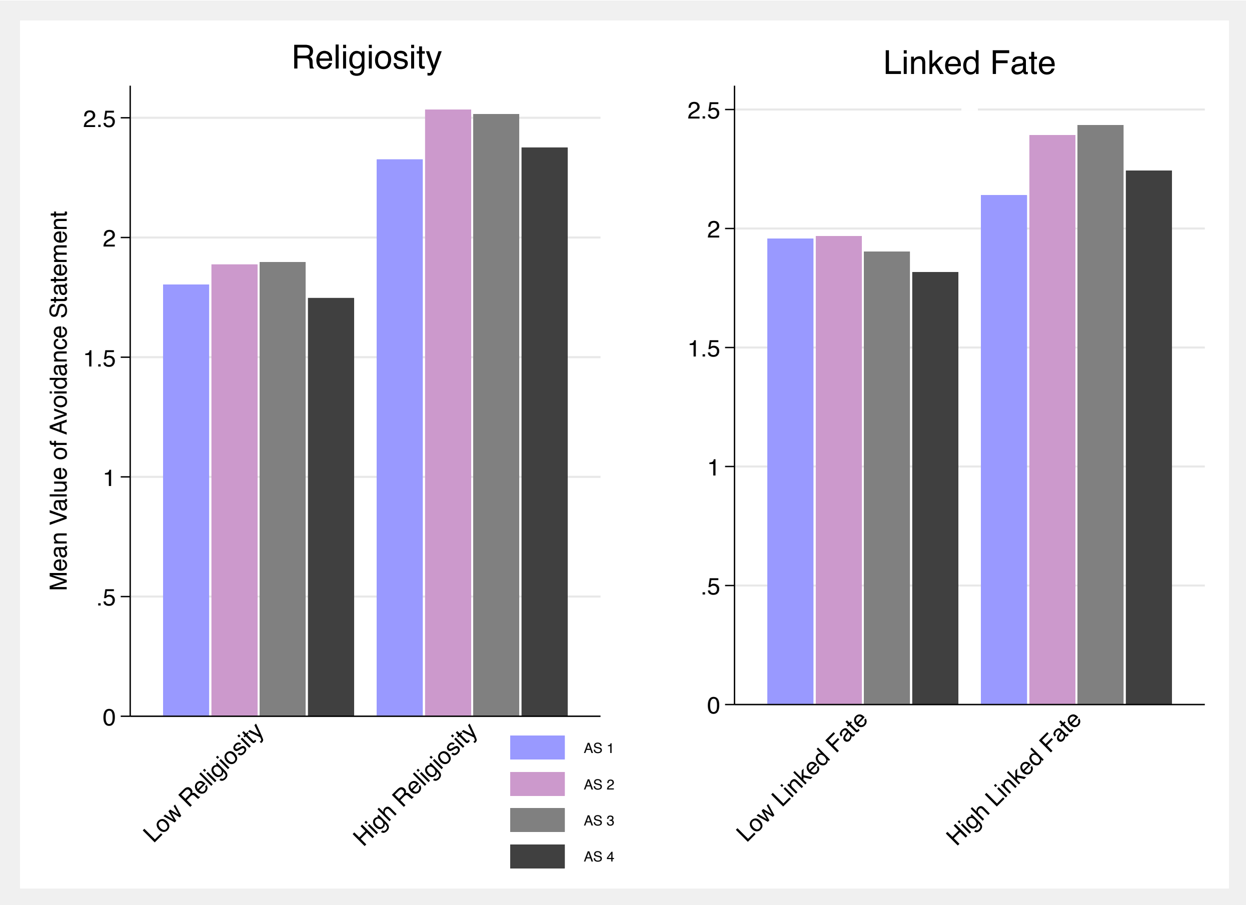

Figure A7: Self-reported avoidance behaviors among Muslim Americans by religiosity and linked fate.

Survey – supplemental tables on societal and political discrimination

We cannot be sure whether those with Twitter accounts belonging to individuals with Arabic names reduced their visibility due to experiences with direct or indirect societal or political discrimination. However, using our survey data, we can begin to test how societal and political discrimination may have shaped these behaviors.

Here, we very briefly build off of Oskooii (2016)'s theory of discrimination that societal discrimination often reduces Muslim American political participation, while political discrimination increases their political participation. Since we are interested in reductions of visibility – or avoidance behaviors – and not political participation, we use the four avoidance statements as our dependent variables. Like Oskooii (2016), we expect experiences with societal discrimination to increase avoidance behaviors in societal contexts (with respect to each of the four dependent variables we examine). We are agnostic about the role of experiences with political discrimination, since the behaviors we measure do not capture avoidance of the political realm or political officials.

We explore two key independent variables of interest. Respondents were asked to evaluate statements with the following prompt: "In the past 12 months, how often have any of the following things happened to you because you are a Muslim." The first independent variable is an aggregated measure of societal discrimination made up of five statements, as follows: (1) You have received poorer service than other people at restaurants and stores, (2) People act as if they are afraid of you, (3) People act as if they are suspicious of you, (4) People called you offensive names or treated you with less respect, (5) You were physically threatened or attacked. The second is an aggregated measure of political discrimination made up of three statements: (1) You were singled out or treated unfairly by airport security, (2) You were singled out or treated unfairly by other government officials or institutions such as the police, and (3) You heard or saw your local government officials or politicians make negative comments about Muslims. Respondents rated each of the statements on a 1-4 Likert scale ranging from 'Never' (1), 'Once in awhile' (2), 'Somewhat often' (3), and 'Very often' (4).

Table A11: Effects of Societal and Political Discrimination on Self-Reported Avoidance Behaviors - Without Controls

	(1) Avoidance Statement 1	(2) Avoidance Statement 2	(3) Avoidance Statement 3	(4) Avoidance Statement 4
Societal Discrimination (aggregate)	0.140***	0.137***	0.0792***	0.140***
	(0.0199)	(0.0212)	(0.0222)	(0.0197)
Political Discrimination (aggregate)	0.0255	0.0369	0.132***	0.0411
	(0.0321)	(0.0342)	(0.0359)	(0.0317)
Constant	0.424**	0.528***	0.520***	0.324*
	(0.138)	(0.147)	(0.154)	(0.136)
N	208	208	208	208
adj. R^2	0.458	0.437	0.404	0.489

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A11 presents an OLS regression examining the effects of the aggregated societal and political discrimination measures on each of the four avoidance statements examined. As each of the four models demonstrates, societal discrimination has a substantive, consistent, and robust effect on each of the avoidance statements examined. Political discrimination, meanwhile, does not similarly predict avoidance behaviors, except for the third statement, pertaining to limiting posts on social media. This finding is provides some insights into the larger findings of this paper; perhaps it is a combination of societal and political discrimination that propelled U.S. Muslims to lessen their visibility during the 2016 election season.

Table A12: Effects of Societal and Political Discrimination on Self-Reported Avoidance Behaviors - With Controls

	(1) Avoidance Statement 1	(2) Avoidance Statement 2	(3) Avoidance Statement 3	(4) Avoidance Statement 4
Societal Discrimination (aggregate)	0.137***	0.137***	0.0713**	0.146***
	(0.0204)	(0.0222)	(0.0238)	(0.0201)
Political Discrimination (aggregate)	0.0278	0.0370	0.134***	0.0405
	(0.0331)	(0.0360)	(0.0385)	(0.0325)
Male	0.131	0.0941	0.0303	0.00311
	(0.116)	(0.126)	(0.134)	(0.114)
White	1.906*	1.854*	-0.406	0.241
	(0.806)	(0.877)	(0.938)	(0.793)
Age	-0.00147	0.00111	-0.00405	0.0111**
	(0.00420)	(0.00457)	(0.00489)	(0.00413)
Income	-0.0795	-0.0464	-0.0445	-0.0330
	(0.0408)	(0.0444)	(0.0475)	(0.0401)
Education	0.0592	0.0735	0.0290	0.0791
	(0.0434)	(0.0472)	(0.0505)	(0.0427)
Democrat	-0.289	-0.0308	0.0381	-0.372*
	(0.151)	(0.164)	(0.175)	(0.148)
Independent	-0.226	0.0717	0.0625	-0.123
	(0.160)	(0.174)	(0.186)	(0.157)
Citizen	-0.217	-0.161	0.0830	-0.169
	(0.199)	(0.216)	(0.231)	(0.195)
Constant	0.836*	0.410	0.631	0.00406
	(0.336)	(0.365)	(0.391)	(0.330)
N	205	205	205	205
adj. R^2	0.477	0.435	0.379	0.519

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When we add controls to the models, the effect of societal discrimination on avoidance behaviors remains strong. As Table A12 demonstrates, standard controls such as male, white, age, income, education, Democrat, Independent, and citizen, do not detract from the important role that societal discrimination plays in shaping self-reported avoidance behaviors. Interestingly, political discrimination continues to not shape avoidance behaviors except for with respect to limiting posts on social media, once again. This finding suggests that future research should work on disentangling the cumulative and interactive effects of societal and political discrimination on avoidance behaviors. Nevertheless, the role of societal discrimination is clear: it plays a similar role in shaping reductions in visibility as it does for reductions in political participation, providing more support for Oskooii (2016)'s theory that nuanced experiences with societal and political discrimination can lead to divergent outcomes.