Effects of Divisive Political Campaigns on the Day-to-Day Segregation of Arab and Muslim Americans*

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Abstract

How have Donald Trump's rhetoric and policies affected Arab and Muslim American behavior? We provide evidence that the de facto effects of President Trump's campaign rhetoric and vague policy positions extended beyond the direct effects of his executive orders. We present findings from three data sources – television news coverage, social media activity, and a survey – to evaluate whether Arab and Muslim Americans reduced their online visibility and retreated from public life. Our results provide evidence that they withdrew from public view: 1) shared locations on Twitter dropped approximately 10 to 20% among users with Arabic sounding names after major campaign and election events and 2) Muslim survey respondents reported increased public space avoidance.

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How do racialized minorities respond to rampant discrimination? Do they retreat from public life or increase their visibility? One body of research indicates that they are worse off psychologically when they perceive greater discrimination or when members of their group are devalued in popular culture (Branscombe, Schmitt and Harvey 1999; Crocker and Major 1989). Those minorities who see prejudice as indications of rejection by the dominant group may internalize negative evaluations, exhibit lower levels of self-esteem, and participate in fewer civic activities (Branscombe, Schmitt and Harvey 1999; Oskooii 2016). In contrast, members of stigmatized groups may react to the dominant group's negative assessments of them by cultivating positive self-esteem and increasing their involvement in activities that enhance their group status (Crocker and Major 1989; Crocker et al. 1989; Branscombe, Schmitt and Harvey 1999; Oskooii 2016).

In this paper, we address the following question: How have Arab and Muslim Americans responded in the public sphere to the widespread national focus on them in the wake of the 2016 presidential campaign? The election season saw presidential front-runners deliver considerable doses of anti-Muslim rhetoric, with Donald Trump proposing a ban on Muslims from entering the country, a national database of all Muslims in the United States, and the wholesale surveillance of mosques; Ben Carson arguing that a Muslim should never be president; and Ted Cruz running on a platform to empower law enforcement to patrol and secure Muslim neighborhoods. Muslim Americans, in turn, experienced unprecedented amounts of discrimination, with imams across the country recommending that they may take extraordinary measures to protect their physical safety and decrease their visibility, such as by taking off the hijab (Calfano, Lajevardi and Michelson 2017).

Yet, we do not actually know whether U.S. Muslims and Arabs followed recommendations from community leaders to hide their identity and stay out of the public eye. On the one hand, we might expect discrimination to cause some people to retreat from the public sphere because discrimination is extremely hurtful. Some members of marginalized groups may avoid public exposure when the rhetoric is negative and is disproportionately concentrated on them to avoid feeling attacked or judged. And, there is evidence that in times of heightened discrimination

American Muslims previously have responded by retreating. For example, surveillance programs after 9/11 led to a chilling effect, increased anxiety and depression, and post-traumatic stress disorder among Arab and Muslim Americans (ACLU 2017; Shamas and Arastu 2013; Amer 2005; Abu-Raiya, Pargament and Mahoney 2011).

However, this retreat from public spheres is not a foregone conclusion. Scholarly work in political science also has shown that in some cases discrimination can powerfully motivate groups, such as Blacks, Asian Americans, and Latinos, to become more engaged in the public sphere and in politics (Barreto and Woods 2005; Pantoja, Ramirez and Segura 2001; Parker 2009; Ramakrishnan 2005; Ramírez 2007; Walker and García-Castañon 2017). Latinos, in particular, have responded to threat and anti-immigration and anti-Latino sentiment by naturalizing, acquiring more political information, protesting, and increasing their rates of turnout (Pantoja, Ramirez and Segura 2001; Pantoja and Segura 2003; Barreto et al. 2009). Similarly, anecdotes about American Muslims in the 2016 election season suggests that a subset responded to the hostile sociopolitical context by mobilizing; some increased their political participation, others started a political action committee, many began writing about politics and Islam on blogs, and a few even ran for political office.[1] And, prior to the 2016 election, Oskooii (2016) found that Muslims reported becoming more active in response to political discrimination; they increasingly registered to vote, protested, and attended political meetings.

Nonetheless, little evidence exists to test how the 2016 campaign's hostile environment affected Arab and Muslim American behavior at the macro and individual levels because rich, systematic, and aggregate data on them is not as readily available as it is for other stigmatized groups (Calfano, Lajevardi and Michelson 2017). This is in part because the U.S. Census does not collect information on religion and those from the Middle East and North Africa must indicate that they are White. [2]

[1]https://www.theatlantic.com/politics/archive/2016/08/muslim-women-trump-islamophobia-ghazala-khan/496925/

[2]The lack of quality data is further exacerbated because surveying Muslim respondents is now more difficult than ever. For example, when contacted to participate in a study by an advocacy group after the election,

In this paper, we overcome these data limitations and analyze public space avoidance among Arab and Muslim Americans in day-to-day and non-political settings by bringing together several data sources: 1) television news coverage of Muslims; 2) social media activity of individuals with Arabic names (both Americans and U.S. residents); and 3) a survey of Muslim Americans. Specifically, we explore whether Arab and Muslim Americans reduced their online visibility and retreated from public life. Together, our results provide macro- and individual-level evidence that Arab and Muslim Americans at least temporarily reduced their visibility in public spaces, both online and offline. We show that this segregation, a previously unmeasured phenomenon, occurred quickly after major presidential campaign events.

Media Discussion of Muslims

As a baseline, our analysis first evaluates news coverage throughout the 2016 election season to identify the major events that were connected to Muslim Americans in order to discern which events and what rhetoric were promulgated against them, and most importantly, *when*.

We summarize major events and news coverage related to Muslim Americans throughout the presidential election by analyzing a large corpus of television news transcripts. We are interested in identifying important events and rhetoric that may have negatively impacted Arab and Muslim Americans. As such, we concentrate on specific, concentrated, and highly salient events that could have affected their behavior. This approach allows us to link specific events that were more highly covered than others in the media to specific dates and then to observed changes in Arab and Muslim behavior on a social media platform. Without concentrated events, or with too many events, this task is made much more difficult. We also want to test whether we can associate important campaign events with changes in social media behavior in an *automated* way. In other words, we allow the news coverage to dictate which events are the most salient. This allows us to associate campaign rhetoric and Arab and Muslim American behavior without assuming that a specific date or event is important ex ante.

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some Muslim respondents feared that they were being registered in Donald Trump's promised "Muslim registry" (Calfano, Lajevardi and Michelson 2017).

To summarize media coverage, we downloaded the universe of available broadcast transcripts from CNN, Fox News, and MSNBC on Lexis Nexis Academic from January 2015 to March 2017. We searched for all mentions of the word 'Muslim' in each transcript and created a term-document matrix limited only to the mention sentence, as well as the sentences before and after.

With this data, we then used a method developed by Hobbs (2017) to scale the text using a combination of a standardized word co-occurrence matrix and word counts.[3] This method orders each of the output dimensions by their contribution to variance in the data, similar to a principal component analysis. While comparable to other text as data techniques, this method has the additional benefit of upweighting very common words so that it effectively summarizes short text on a focused topic (e.g. here, a few sentences on 'Muslims' in the news media). A specific advantage of this and other scaling methods over topic models (Blei, Ng and Jordan 2003; Roberts, Stewart and Tingley 2014) is that the user does not have to specify the number of topics and therefore has very little control over the output. The output, moreover, will ultimately guide us in deciding which events to examine in our social media analysis.

Table 1 displays the keywords of the dimensions extracted using this process.[4] A substantial amount of discussion of Muslims in the transcripts focused on the Middle East and both international and domestic terrorism. Domestic-focused coverage on Muslim Americans and U.S. politics concentrated on three major events: 1) Donald Trump's proposed Muslim ban and immigration policy, 2) Khizr Khan's speech at the Democratic National Convention, and, to a much lesser extent, 3) policing and Ted Cruz's proposal to surveil Muslim American commu-

[3]This method is related to familiar text scaling and ideal point methods used in political science, such as WordFish (Slapin and Proksch 2008) and Wordscores (Laver, Benoit and Garry 2003).

[4]The keywords in this method are identified using the output from one side of a singular value decomposition. Slightly differently than in Hobbs (2017), which analyzes open-ended survey responses, the keywords were identified by multiplying the square root Euclidean norm of the scores from the word embedding side of the output by the specific values on the co-occurrence side of the output. This allows us to summarize highly specific clusters of words, rather than the general ideas of interest in open-ended survey response summaries. Figures A1 and A2 show the full output on which these keywords are based.

Words appearing with mention of "Muslim(s)" in news coverage					
Dimension 1		Dimension 2			Dimension 5
mexicans	brussels	temporary	soldier	...	police
wall	mosques	immigration	khan	...	cruz
latinos	paris	countries	iraq	...	ted
trump	young	different	gold	...	neighborhoods
entering	bernardino	entering	killed	...	enforcement
donald	san	communities	family	...	terror
ban	law	idea	father	...	state
women	within	shutdown	star	...	surveillance
muslims	europe	complete	parents	...	belgium
judge	extremism	total	fallen	...	intelligence
mexican	places	problem	convention	...	correspondent
khan	victims	proposed	son	...	patrol
shutdown	violent	sort	captain	...	plan
banning	enforcement	radical	women	...	security
ryan	acts	policy	muslim	...	former

Table 1: The dimensions in this figure were estimated using Hobbs (2017)'s text scaling method. The method is similar to principal component analysis. The first dimension of the output identifies a split between coverage of the U.S. presidential campaign and coverage of terrorist attacks. The second dimension of the output shows discussion of Trump's proposed immigration ban. These remaining dimensions are displayed in the appendix.

nities.[5] In general, discussion of Muslims was closely associated with mentions of Mexicans, Donald Trump's proposed Mexican border wall, women, and immigrants.

Overall, this text analysis suggests that Trump's 'Muslim ban' comments were much more salient than any other campaign events. To further evaluate the salience of the 'Muslim ban' discussion, we compare mentions of 'Muslim ban' on all of Twitter[6] to any mention of 'Muslim' in the news media. As Figure A3 shows, mentions of 'Muslim' in any context in the media were closely related to 'Muslim ban' discussions on Twitter.

Evidence from Twitter

Next, we turn to our substantive question of interest: how did Arab and Muslim Americans respond, in the aggregate, to events and discriminatory rhetoric in the 2016 election season?

[5]The Ted Cruz cluster was prominent during the first half of 2016 (when we first ran this analysis), but faded in importance after the Republican primaries.

[6]Mentions were collected using Crimson Hexagon, rather than the Streaming API.

Specifically, we evaluate whether the visibility of Arab and Muslim activity on Twitter shifted at all in relation to salient events highlighted in the previous section, such as the Muslim ban.

We assembled a corpus of all geotagged tweets in the United States from 2015 through the middle of February 2017 to identify Arabic-named Twitter users who shared their precise location on the site.[7] Because Muslims are a diverse group on national origin and racial dimensions, and because there is no distinctly Muslim dictionary that encompasses possible Muslim names, we use a name dictionary with distinctively Arabic names as a loose proxy for 'Muslim.'[8]

After identifying those accounts belonging to individuals with Arabic names, we reduced the number of accounts to U.S.-only users by parsing locations shared in the Twitter account profiles. This allowed us to remove users who posted a tweet from the United States, but who lived elsewhere. We did not use language as our primary filtering method because the language of tweets is algorithmically assigned by Twitter and these language assignments often change abruptly (although, as we describe below, we do use this information in a robustness check in the appendix). This name and location based filtering method identified 3,845 geotagging Twitter users for our study.

Many of these precise locations are shared through services other than Twitter, such as Foursquare and Instagram.[9] For example, Foursquare shares appear with the words "I'm at" by default and tend to be restaurant visits and ordinary social activities. Instagram posts are accompanied by a photo and can be associated with the location of the photo. Geotags from

[7]These geotagged tweets were collected from Twitter's public streaming API by setting a boundary box around the United States and collecting tweets appearing within that box as they were posted to the site. When restricted to the United States, the output of this method falls below the API limit.

[8]We believe that this is the best - though admittedly imperfect - way of observing online Muslim activity. While many Arabs are Christian, the U.S. Arab Muslim population has grown rapidly with the removal of the quota system and more lenient immigration laws. Combined with the fact that the United States admitted a record number of Arab Muslim refugees in 2016, it is likely the case that many of these users are Muslim. Moreover, we guess that around 1 of 4 of these accounts are Black Americans with names of Arabic origin. This aligns nearly perfectly with the Pew Research Center's estimates of the Black Muslim population in America: 20%.

[9]The original source of a tweet is provided in the data from the Twitter API.

these sites accounted for 73% of the data (57% Instagram and 16% Foursquare).

We observe these precise geotags over time as a proxy for 1) how much U.S. Arabs were out in public places during and after the 2016 presidential campaign and 2) whether they publicly shared their exact location or adjusted their visibility by altering their privacy settings to hide it. More broadly, alterations in privacy settings measure concern for personal safety among Arab Americans and residents. This proxy reflects warnings by the United States Army and others that sharing location online compromises individual and family privacy and personal security.[10]

Figure 1 displays the number of daily unique geo-tagging Arabic-named U.S.-based users from August 2015 through February 2017 and allows us to assess whether U.S. Arabs avoid public spaces or altered their privacy settings to adjust their visibility. The purple line denotes that shared locations by Arabic-named Twitter users dropped by 10 to 20% after December 2015 and 10% between the 2016 election and Donald Trump's 'Muslim ban' executive order in January 2017.

To avoid imposing specific dates for the time series discontinuities and to assess whether structural breaks in the time series lined up with media coverage of Muslims in the 2016 campaign, we used the automated break point identification method described in Bai and Perron (2003) to identify discontinuities in the data. With the number of break points set to 2, December 2, 2015 and November 14, 2016 were identified as breakpoints in the time series. December 2 was the San Bernardino terror attack and the event that immediately preceded Donald Trump's Muslim ban statement on December 7. On December 2nd, Donald Trump's statements included that many people witnessed Muslims celebrating on their roofs after the 9/11 attack[11] and that to defeat ISIS terrorists "you have to take out their families."[12] A decline in the geo-tags begins on December 2 and then drops around 10% within a few days after the 'Muslim ban' statement. We once again observe declines in geo-tags after the date of the 2016

[10]https://www.army.mil/article/75165/geotagging_poses_security_risks

[11]https://twitter.com/realdonaldtrump/status/672149956208271360

[12]http://insider.foxnews.com/2015/12/02/donald-trump-fox-and-friends-we-have-take-out-isis-terrorists-families

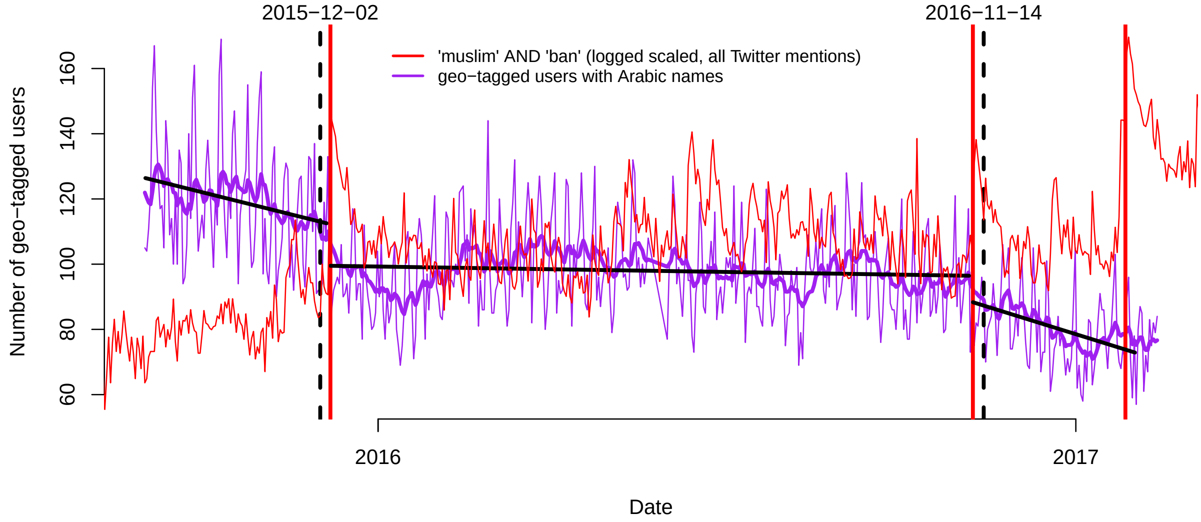

Figure 1: The vertical red lines are 1) Donald Trump's statement "calling for a total and complete shutdown of Muslims entering the United States" 2) the 2016 election and 3) the first executive order/'Muslim ban.' Total number of unique geo-tagged, Arabic sounding named users with US location in profile, August 2015 through mid February 2017: 3,845. Automatically detected time series breaks are shown as dotted lines. December 2 was the San Bernardino terror attack and the event that immediately preceded Donald Trump's Muslim ban statement on December 7. On December 2nd, Donald Trump's statements included that many people witnessed Muslims celebrating on their roofs after the 9/11 attack[10] and that to defeat ISIS terrorists "you have to take out their families"[11]. The time series was smoothed (bold line) using an adjustment for weekly seasonality.

presidential election, which continue into 2017.

That these drops occurred immediately after major campaign statements and election events is suggestive that campaign rhetoric negatively affected Arab and Muslim Americans, who responded by reducing their visibility. It is still important to rule out alternate explanations, however. In particular, some Instagram users were logged out of their accounts on December 2 and received incorrect error messages when they tried to log back in.[13] In the appendix, we assess whether this bug could have driven the observed drop on December 2, and find a large drop among Arabic speakers with Arabic sounding names on both Instagram and other platforms, along with a drop among all people with Arabic sounding names for geotags not from Instagram. These same drops in activity were smaller or absent in a matched control

[13] https://www.independent.co.uk/life-style/gadgets-and-tech/news/instagram-hacked-changed-password-a6759046.html

group, despite the control group potentially containing other minorities due to a requirement that users have names unique at the state-level (see appendix for details). This increases our confidence that the sustained drop was driven by the December 2 San Bernardino attack and rhetoric surrounding it, including the December 7 ban statement, rather than the Instagram software glitch.

Another lingering concern is that geolocated tweets constitute less than 1% of all tweets on Twitter and are not representative of the overall population of Twitter users (Sloan and Morgan 2015). As a robustness check, we include in the appendix an analysis of the representativeness of the sample by replicating our analysis with users who were linked to voter records.[14] This data includes basic demographic information on those individuals with distinctively Arabic names in our study, and we show that they very closely resemble the racial identification of Muslim Americans in separate research by the Pew Research Center.[15] Our analysis of the voter record data shows drops in activity among people with Arabic names in early December, but not after the 2016 election. This suggests that the drop in early December applied to both citizens and non-citizens, while the decline after the 2016 election might have been specific to non-citizens. However, these tests are not well-powered among this small subset of users with both unique names and a record in the voter file, at least when compared to drops among others with uncommon names and similar demographic characteristics.

Finally, we note that although the number of geotagging Arabic named users declined, some users began posting more geotagged tweets after the 2016 election (see Figure A6). However,

[14]Because geotagging Twitter users are a small subset of the Twitter population, we include in the appendix descriptive statistics for the Arabic named Twitter users who could be uniquely linked to voter records. These users were dramatically more male than female due to our Arabic sounding name filter, but closely matched Pew's published estimates of the racial makeup of American Muslims and geotagging users in our sample were about the same age as the average for all Arabic sounding name users on Twitter. Previous analyses have shown that geotagging users are typically much younger than the average Twitter user and that geotagging varies by language and location (Sloan and Morgan 2015), but we do not see a difference in our sample. Note that our results are themselves also a demographic difference in geotagging; those with Arabic names have geotagged less over time.

[15]http://www.pewforum.org/2017/07/26/demographic-portrait-of-muslim-americans/

these spikes in activity sharply declined with the January 2017 announcement that the administration would soon sign the executive order temporarily halting refugee immigration and from some Muslim majority countries.[16] These tweets were not obviously political. We show a text analysis in the appendix, where all dimensions appear to be related to location or leisure activities.

These asides notwithstanding, the results presented in this section together provide macro-level evidence that U.S.-based Arabic-named Twitter users altered their privacy settings and reduced their visibility in response to salient events occurring throughout the 2016 presidential campaign and election; namely Donald Trump's 'Muslim ban' statement (along with other statements preceding it) and the election date itself. This decreased visibility and segregation from ordinary society, moreover, occurred quickly and lasted for months at each of the two timepoints examined.

Survey of Muslim Americans

Next, we turn to a survey on Muslim Americans to explore whether the macro-level phenomenon of Arabic named Twitter users reducing their visibility can be substantiated at the individual-level. There are reasons to expect that experiences with societal discrimination would lead Muslim Americans to avoid or withdraw from public spaces. Oskooii (2016) emphasizes the need for scholars to contemplate that discrimination may result in divergent outcomes, depending on the type of discrimination being examined; when faced with direct societal, rather than political discrimination, Oskooii (2016) finds that U.S. Muslims participate in politics less. While we are not looking at reductions in political participation, Oskooii (2016) lays important groundwork for theory building.

Over the time period studied, important and discriminatory rhetoric arguably had fostered a hostile environment, where acts that openly targeted minorities became more commonplace. Scholarly evidence suggests that Trump's racist speech normalized ordinary people adopting

[16]Figure A5 shows that state-level geotags (e.g. Los Angeles, California, rather than a specific latitude and longitude) spiked both after the 2016 election and before the executive order.

similar language; Schaffner (2018) finds that being exposed to Trump's quotes causes individuals to say more offensive things, not only about the groups Trump targeted, but about other identity groups as well. There is also evidence that dehumanizing and anti-Muslim attitudes shaped Trump support in the 2016 election (Lajevardi and Oskooii 2018; Lajevardi and Abrajano 2018). Considering these reasons and the increasing rate of hate crimes against Muslims that manifested after the election (SPLC 2017), it is entirely conceivable that the environment made U.S. Muslims concerned for their interactions with ordinary society, reduce their visibility, and less willing to publicly share their information online.

We briefly detail results from a survey on 208 Muslim Americans in February 2017 conducted through Survey Sampling International. We designed the survey to evaluate whether Muslim Americans reported avoidance and segregation behaviors during the 2016 campaign season. We note that there are two important downsides to an opt-in survey of this nature: 1) the survey does not allow for much inference because the sample is small and because it was only administered in one wave, and 2) respondents are not at all guaranteed to be representative of the U.S. Muslim population.[17] However, the survey serves to corroborate or dispel the findings presented so far.

We find that Muslim Americans reported having responded to discrimination in the public sphere during this time period by retreating. Reflecting on their behavior over the past 12 months, respondents across the board self-reported that they had avoided interactions with members of other groups, avoided interactions with members of other political parties, limited their posts on social media, and less frequently visited public places (such as restaurants, shopping malls, and parks) more than once in a while (see Table A10). In line with the scholarship on foreign and American Muslims, we also explore how religiosity (Jamal 2005; Barreto and Dana 2008; Barreto and Bozonelos 2009; Dana, Barreto and Oskooii 2011; Dana, Wilcox-Archuleta and Barreto 2017; Oskooii and Dana 2017) and linked fate (Barreto, Masuoka and Sanchez 2008; Barreto and Bozonelos 2009) affected self-reported avoidance shifts in behav-

[17] See footnote 2 and Calfano, Lajevardi and Michelson (2017) for a discussion on the difficulties of surveying Muslim Americans.

ior.[18] Similar to other studies, we find that more religious respondents and those with high linked fate are more insulated; they were significantly more likely than their counterparts to report avoidance behaviors (see Figure A7).

We triangulate the results from the Twitter and voter record analyses with the survey, which provides further corroborating individual-level evidence that U.S. Muslims are retreating. Future research should unpack the mechanism behind this decline in visibility. While we posit that the withdrawal we observe may be due to feelings of threat that individuals in ordinary society are targeting them, we cannot be sure. Our results only speak to the fact that the avoidance behaviors reported in the survey extend to both the social and political contexts, and support the observed drops in Twitter geo-tags and tweets.

Implications

While these findings are far from the final say on how Arab and Muslim Americans have responded to the negative rhetoric and policies fostered in the 2016 presidential election, they are instructive. Our work makes several contributions to the existing literature on the macro-level measurement of Arab and Muslim American behavior. For the most part, studies have not evaluated macro-level Arab and Muslim American behavior because demographic and statistical data on this group does not readily exist and is very difficult to assemble (see Cho, Gimpel and Wu (2006) for an important exception). By examining the universe of available Twitter accounts geolocating to the United States and subsetting to probable U.S. 'Arab' and 'Muslim' accounts, we provide a unique way of identifying and tracing whether their ordinary social activity became more or less visible without relying on self-reported data. We note that scholars examining hard to reach populations – and especially those about whom information cannot be

[18] More detailed explanations of the variables, their coding, and their limitations can be found in the appendix. We note that this question is at risk of being highly unreliable insofar as it is a self-reported measure, which asks respondents to reflect on their behavior over the past year. We present these results to provide suggestive and triangulating, rather than conclusive, evidence.

readily acquired – can be well served by testing hypotheses against findings from multiple data sources.

Our results provide insight on a central question surrounding the consequences of the 2016 election campaign: Did Arab and Muslim Americans respond to rampant discrimination by retreating from public life or by increasing their visibility? We utilize individual- and macro-level evidence to demonstrate that they at least temporarily altered their behavior and retreated, in light of the discrimination they faced throughout the 2016 presidential election season. This paper is the first to demonstrate that this discrimination may have resulted in isolating and restrictive behaviors; they reduced their online visibility and reported fading from the public sphere. While the prevailing wisdom in political science would lead us to expect members of stigmatized communities to take action rather than resign from the public sphere in light of political discrimination, this study provides further support for Oskooii (2016)'s theory that discrimination may result in divergent outcomes.

Our findings also demonstrate that retreat from public spaces can occur in a matter of days to weeks after a major political event, and can be sustained for many months, perhaps even years, after the event. Nevertheless, the study of perceived discrimination is complex (Oskooii 2016), and we therefore need more research to better understand the conditions under which discrimination ignites activism or results in withdrawal from sociopolitical life. Future studies will also be well-served by implementing survey experiments that manipulate direct and indirect exposure to varying levels of societal and political discrimination, which would only build a more robust scholarship on the findings presented here.

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Online Appendix

Transcript text analysis – supplemental figures and tables

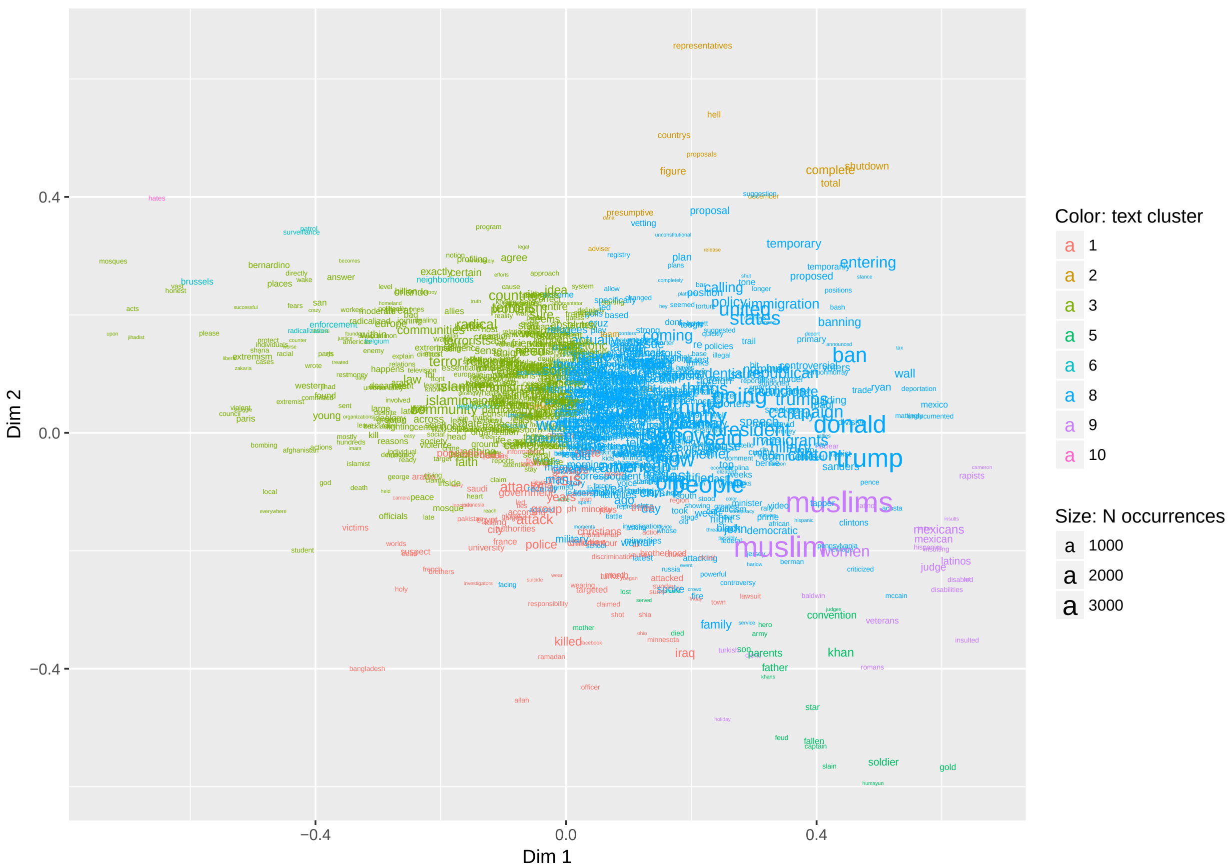

Figure A1: *Word co-occurrence view of word clusters - top 2 dimensions.* Colors are from posthoc k means clustering that used 10 clusters on the top 10 dimensions of the output. These colors are used only to make the figure somewhat easier to read and are not used in the analyses. The 'specific' keywords 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.

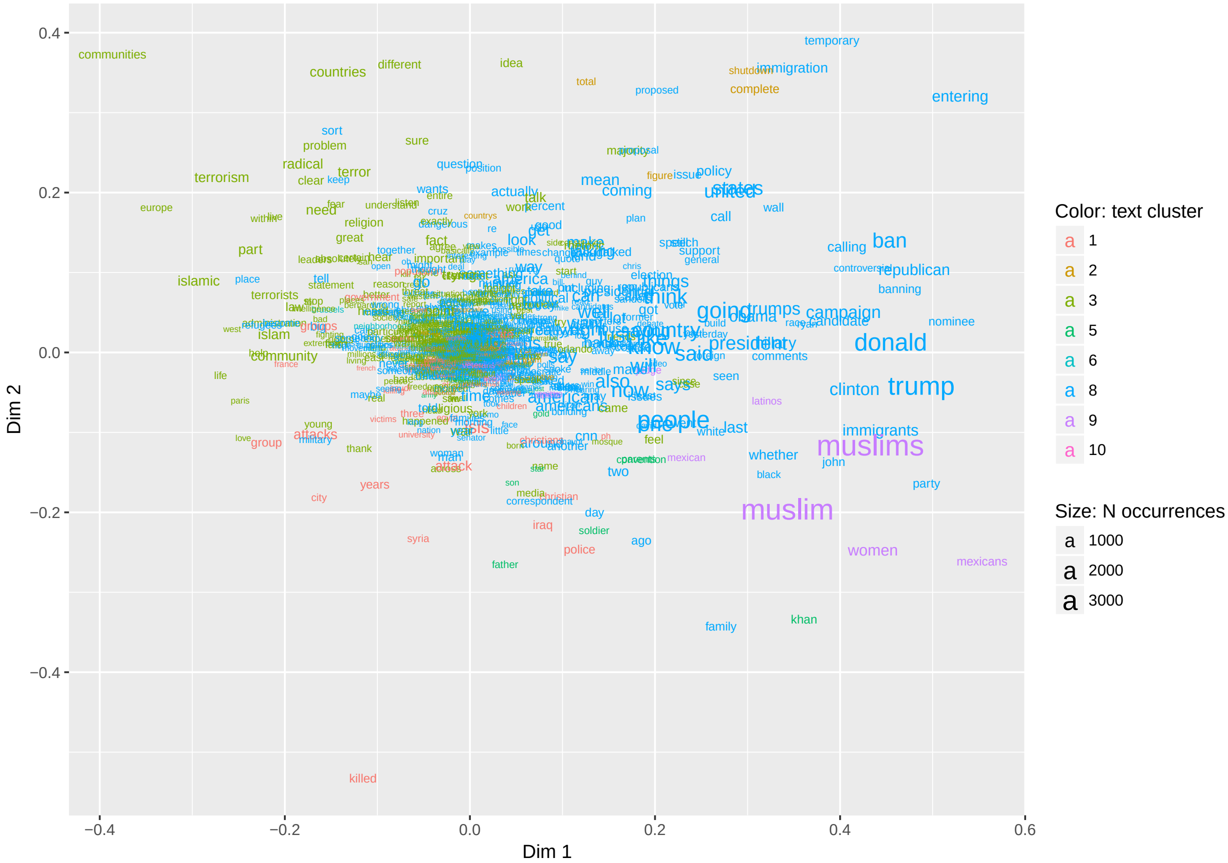

Figure A2: *Word count view of word clusters - top 2 dimensions.* Colors are from posthoc k means clustering that used 10 clusters on the top 10 dimensions of the output. These colors are used only to make the figure somewhat easier to read and are not used in the analyses. The 'common' keywords in the 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

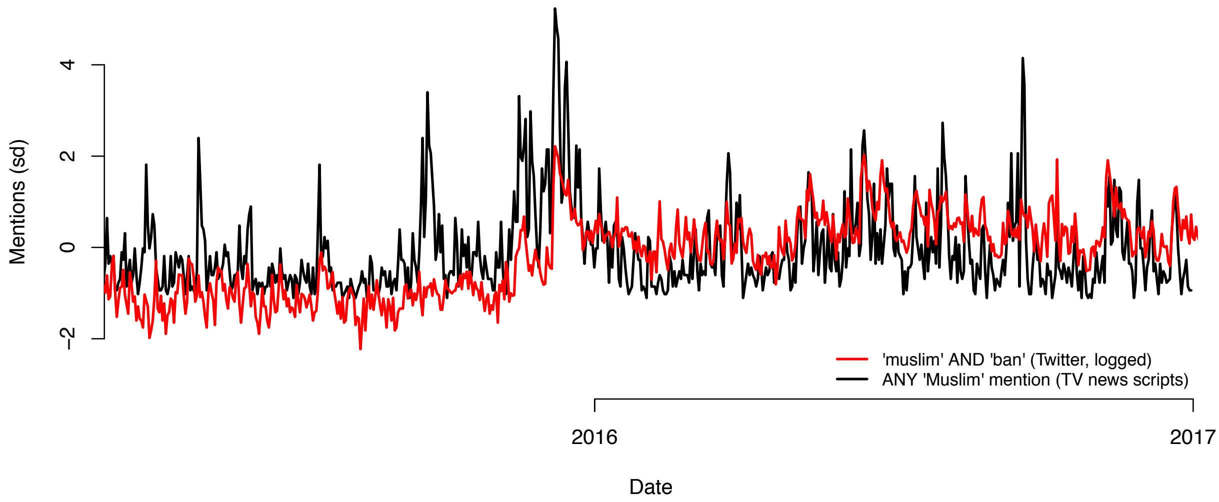

Figure A3: *Comparison of Television News Coverage of Muslims and Twitter mentions of a Muslim ban.* In black, the number of mentions of 'Muslim' in the TV news scripts in standard deviation units; in red, the logged number of mentions of 'Muslim' and 'ban' on Twitter in standard deviation units.

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.

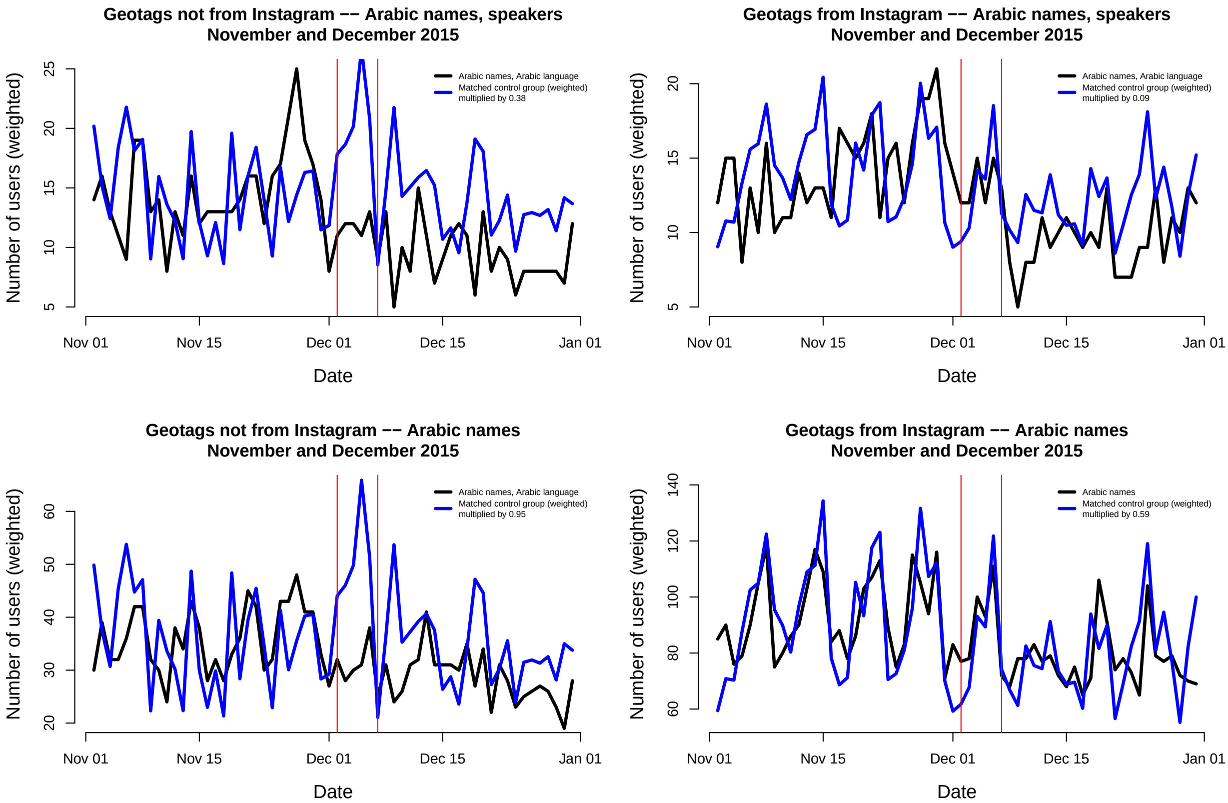

Figure A4: *Drops in Arabic name, Arabic name and language, and Arabic name voter samples compared to a matched control group by source of tweet.*

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

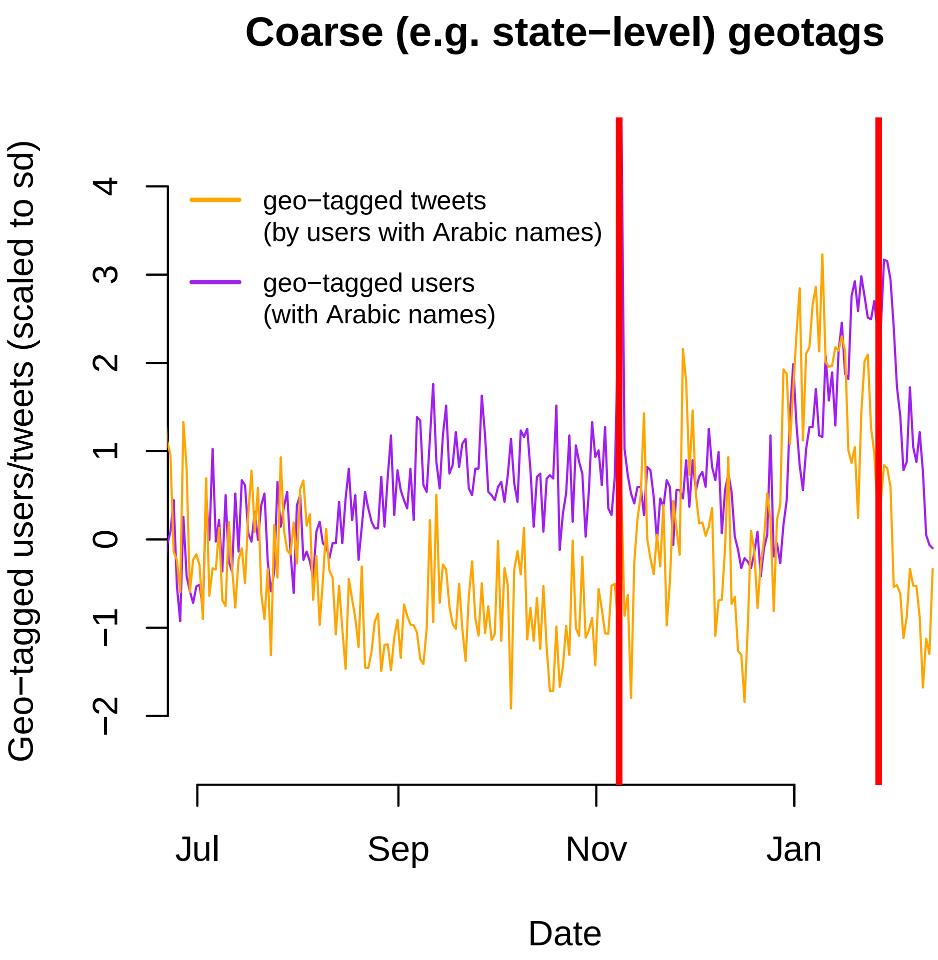

Figure A5: *Other geotagged tweets (i.e. state-level geotags) by Arabic named Twitter users.* The red lines are 1) the 2016 election 2) the executive order.

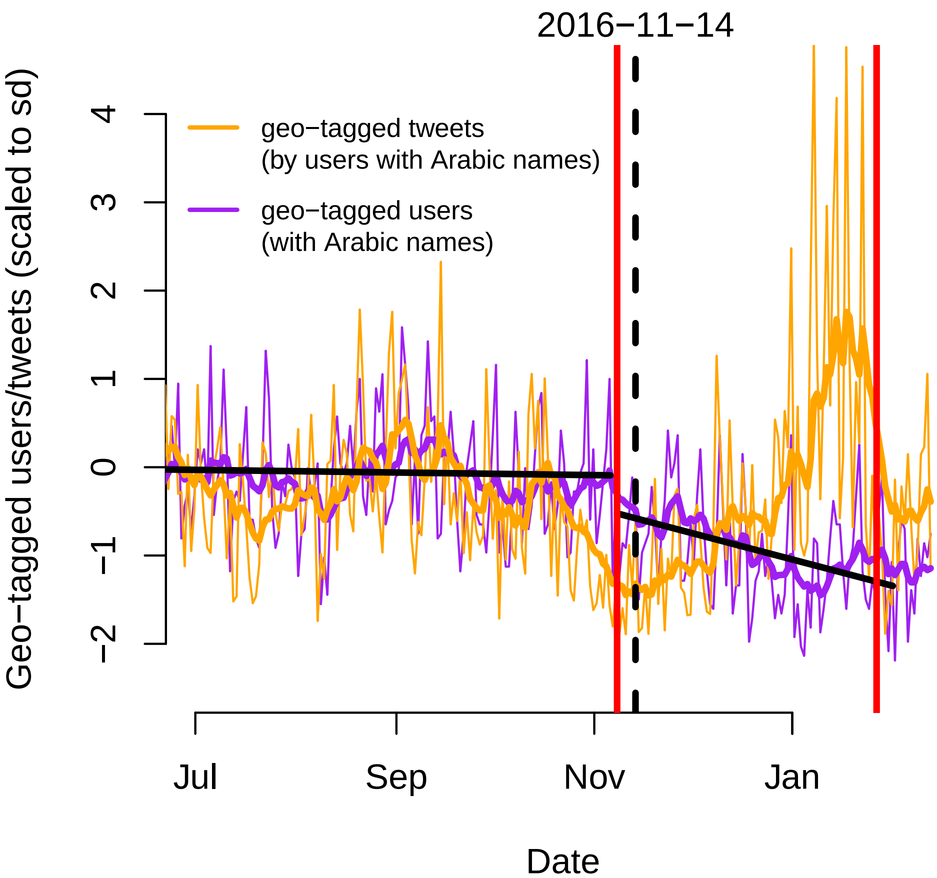

Figure A6: Vertical black dotted lines identified using the method described in Bai and Perron (2003) with the number of breaks set to two. The red lines are 1) the 2016 election 2) the executive order.

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

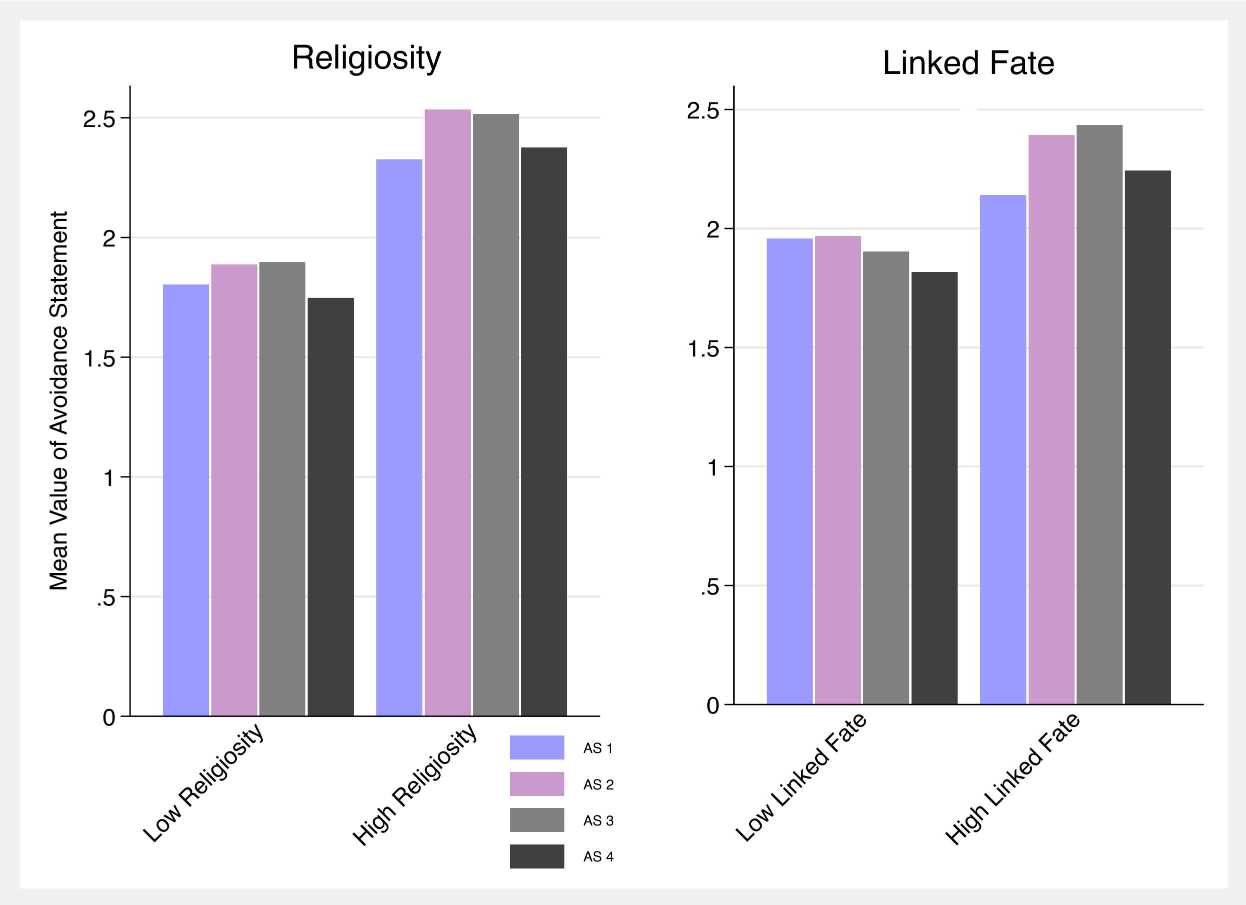

Figure A7: Self-reported avoidance behaviors among Muslim Americans by religiosity and linked fate.

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.