# From Hashtag to Hate Crime: Twitter and Anti-Minority Sentiment

## Online Appendix

*By* Karsten Müller and Carlo Schwarz

## Appendix 1: Additional Details on Data

**Table A.1—: Descriptive Statistics (Main Variables)**

| | Mean | Std. Dev. | Min. | Median | Max. | N |
|---|---|---|---|---|---|---|
| **Hate crime and Twitter variables** | | | | | | |
| Δ Log(Hate crimes against Muslims) | 0.03 | 0.14 | -0.55 | 0.00 | 1.36 | 3,108 |
| Log(Twitter users) | 5.28 | 1.76 | 0.00 | 5.12 | 12.34 | 3,108 |
| Log(SXSW followers, March 2007) | 0.06 | 0.32 | 0.00 | 0.00 | 4.98 | 3,108 |
| Log(SXSW followers, Pre) | 0.02 | 0.18 | 0.00 | 0.00 | 3.61 | 3,108 |
| **Demographic controls** | | | | | | |
| % aged 20-24 | 0.06 | 0.02 | 0.01 | 0.06 | 0.27 | 3,108 |
| % aged 25-29 | 0.06 | 0.01 | 0.03 | 0.06 | 0.15 | 3,108 |
| % aged 30-34 | 0.06 | 0.01 | 0.03 | 0.06 | 0.12 | 3,108 |
| % aged 35-39 | 0.06 | 0.01 | 0.03 | 0.06 | 0.11 | 3,108 |
| % aged 40-44 | 0.06 | 0.01 | 0.02 | 0.06 | 0.10 | 3,108 |
| % aged 45-49 | 0.06 | 0.01 | 0.02 | 0.06 | 0.09 | 3,108 |
| % aged 50+ | 0.39 | 0.07 | 0.11 | 0.39 | 0.75 | 3,108 |
| Population growth, 2000-2016 | 0.06 | 0.18 | -0.43 | 0.03 | 1.32 | 3,108 |
| **Geographical controls** | | | | | | |
| Population density | 261.27 | 1733.47 | 0.10 | 45.60 | 69468.40 | 3,108 |
| Log(County area) | 6.53 | 0.86 | 0.69 | 6.47 | 9.91 | 3,108 |
| Distance from Austin, TX (in miles) | 1450.64 | 612.61 | 5.04 | 1464.66 | 3098.88 | 3,108 |
| **Race and religion controls** | | | | | | |
| % white | 0.77 | 0.20 | 0.03 | 0.84 | 0.98 | 3,108 |
| % black | 0.09 | 0.14 | 0.00 | 0.02 | 0.85 | 3,108 |
| % native American | 0.02 | 0.06 | 0.00 | 0.00 | 0.90 | 3,108 |
| % Asian | 0.01 | 0.02 | 0.00 | 0.01 | 0.37 | 3,108 |
| % Hispanic | 0.09 | 0.14 | 0.01 | 0.04 | 0.96 | 3,108 |
| % Muslim | 0.00 | 0.01 | 0.00 | 0.00 | 0.30 | 3,108 |
| **Socioeconomic controls** | | | | | | |
| % below poverty level | 16.74 | 6.58 | 1.40 | 16.00 | 53.30 | 3,108 |
| % unemployed | 5.50 | 1.94 | 1.80 | 5.30 | 24.10 | 3,108 |
| Gini index | 0.44 | 0.03 | 0.33 | 0.44 | 0.65 | 3,108 |
| % uninsured | 13.32 | 5.28 | 1.80 | 12.80 | 49.00 | 3,108 |
| Log(Median household income) | 10.72 | 0.24 | 9.87 | 10.71 | 11.72 | 3,107 |
| % employed in agriculture | 0.01 | 0.03 | 0.00 | 0.00 | 0.58 | 3,108 |
| % employed in IT | 0.01 | 0.01 | 0.00 | 0.01 | 0.21 | 3,108 |
| % employed in manufacturing | 0.16 | 0.13 | 0.00 | 0.13 | 0.72 | 3,108 |
| % employed in nontradable sector | 0.29 | 0.11 | 0.00 | 0.28 | 1.00 | 3,108 |
| % employed in construction/real estate | 0.07 | 0.05 | 0.00 | 0.06 | 1.00 | 3,108 |
| % employed in utilities | 0.04 | 0.05 | 0.00 | 0.03 | 1.00 | 3,108 |
| % employed in business services | 0.16 | 0.07 | 0.00 | 0.15 | 0.95 | 3,108 |
| % employed in other services | 0.25 | 0.10 | 0.00 | 0.24 | 1.00 | 3,108 |
| % adults with high school degree | 34.77 | 7.07 | 7.50 | 35.20 | 54.80 | 3,108 |
| % adults with graduate degree | 7.05 | 4.12 | 0.00 | 5.80 | 44.40 | 3,108 |

**Table A.1—: Descriptive Statistics (Main Variables, Continued)**

| | Mean | Std. Dev. | Min. | Median | Max. | N |
|---|---|---|---|---|---|---|
| **Media controls** | | | | | | |
| % watching Fox News | 0.26 | 0.01 | 0.23 | 0.26 | 0.30 | 3,107 |
| % watching prime time TV | 0.43 | 0.01 | 0.40 | 0.43 | 0.47 | 3,107 |
| **Election control** | | | | | | |
| Republican vote share, 2012 | 0.60 | 0.15 | 0.06 | 0.61 | 0.96 | 3,108 |
| **Crime controls** | | | | | | |
| Violent crime rate | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 3,108 |
| Property crime rate | 0.02 | 0.01 | 0.00 | 0.01 | 0.10 | 3,108 |
| **Other hate crime variables** | | | | | | |
| $\Delta$ Log(Total hate crimes) | 0.09 | 0.39 | -1.95 | 0.00 | 2.34 | 3,108 |
| $\Delta$ Log(Hate crimes against Hispanics) | 0.01 | 0.17 | -1.65 | 0.00 | 1.32 | 3,108 |
| $\Delta$ Log(Other ethnicity-based hate crimes) | -0.00 | 0.17 | -2.60 | 0.00 | 1.43 | 3,108 |
| $\Delta$ Log(Racially motivated hate crimes) | 0.06 | 0.34 | -1.69 | 0.00 | 2.13 | 3,108 |
| $\Delta$ Log(Hate crimes based on sexual orientation) | 0.01 | 0.22 | -1.32 | 0.00 | 1.92 | 3,108 |
| $\Delta$ Log(Hate crimes against other religions) | 0.05 | 0.24 | -1.46 | 0.00 | 1.68 | 3,108 |
| Log(Total hate crimes, ADL data) | 0.23 | 0.64 | 0.00 | 0.00 | 5.38 | 3,108 |

**Table A.2—: Summary Statistics for Time Series**

| Variable | Mean | SD | p50 | Min | Max | N |
|---|---|---|---|---|---|---|
| **Trump tweets** | | | | | | |
| Log(1+Muslim Trump tweets) | 0.08 | 0.25 | 0.00 | 0.00 | 1.79 | 365 |
| Log(1+Trump tweets) | 1.95 | 0.58 | 0.00 | 1.95 | 3.30 | 365 |
| Muslim Trump tweets (dummy) | 0.09 | 0.29 | 0.00 | 0.00 | 1.00 | 365 |
| **Hate crimes against Muslims (1 + natural logarithm)** | | | | | | |
| All types | 0.43 | 0.45 | 0.00 | 0.69 | 1.61 | 365 |
| Assault | 0.29 | 0.40 | 0.00 | 0.00 | 1.61 | 365 |
| Vandalism | 0.14 | 0.29 | 0.00 | 0.00 | 1.39 | 365 |
| Theft | 0.01 | 0.09 | 0.00 | 0.00 | 1.10 | 365 |
| Burglary | 0.01 | 0.07 | 0.00 | 0.00 | 0.69 | 365 |
| Robbery | 0.01 | 0.09 | 0.00 | 0.00 | 0.69 | 365 |
| **Other hate crimes (1 + natural logarithm)** | | | | | | |
| All hate crimes | 2.91 | 0.27 | 2.08 | 2.94 | 3.58 | 365 |
| Other ethnicity | 0.38 | 0.45 | 0.00 | 0.00 | 1.79 | 365 |
| Race | 2.22 | 0.37 | 0.69 | 2.30 | 3.00 | 365 |
| Sexual orientation | 1.23 | 0.48 | 0.00 | 1.39 | 2.40 | 365 |
| Religion (excl. Muslims) | 1.28 | 0.50 | 0.00 | 1.39 | 2.83 | 365 |
| **TV news coverage (1 + natural logarithm)** | | | | | | |
| Muslim mentions (total) | 3.71 | 0.64 | 0.69 | 3.69 | 5.26 | 365 |
| Muslim mentions (Fox News) | 2.75 | 0.66 | 0.00 | 2.77 | 4.29 | 365 |
| Muslim mentions (CNN) | 2.24 | 0.94 | 0.00 | 2.30 | 4.29 | 365 |
| Muslim mentions (MSNBC) | 2.75 | 0.66 | 0.00 | 2.77 | 4.26 | 365 |
| **Trump's golfing** | | | | | | |
| Trump golfs | 0.25 | 0.43 | 0.00 | 0.00 | 1.00 | 365 |
| Trump golfs (NYT only) | 0.24 | 0.43 | 0.00 | 0.00 | 1.00 | 365 |
| Trump golfs (alternative coding) | 0.25 | 0.44 | 0.00 | 0.00 | 1.00 | 365 |
| Golf holiday | 0.16 | 0.37 | 0.00 | 0.00 | 1.00 | 365 |
| Golf in previous week | 0.75 | 0.43 | 0.00 | 1.00 | 1.00 | 365 |
| **Other control variables** | | | | | | |
| Google searches about Muslims (PC) | -0.27 | 1.98 | -2.11 | -0.59 | 21.51 | 365 |
| Terror attack in the West | 0.03 | 0.17 | 0.00 | 0.00 | 1.00 | 365 |

*Notes:* This table presents descriptive statistics for the IV sample. The sample year is 2017. *1+log* or *1+natural logarithm* means that the logarithm of any variable is calculated with 1 added inside. The data on hate crimes come from the FBI hate crime statistics. Data on Trump's golfing come from the New York Times, the official White House presidential schedule, and trumpgolfcount.com. *Google searches about Muslims (PC)* is the first principal component of Google trends for the key words "islam", "mosque", "muslim", "refugee", "sharia", and "terror". We use these same keywords as measures of TV news attention based on data from the internet archive. The sources for the number of terror attacks is the Global Terrorism Database. See the online appendix for more details on data and variable construction.

### A.1. FBI Hate Crime Data

As described in the Section I, the FBI uses a two-tier decision making process for classifying hate crimes. FBI (2015) describes the decision making process in the following way:

> "Once the development of this collection was complete, the FBI UCR Program surveyed state UCR Program managers on hate crime collection procedures used at various law enforcement agencies which collected hate crime data employing a two-tier decision-making process. The first level is the law enforcement officer who initially responds to the alleged hate crime incident, i.e., the "responding officer" (or "first-level judgment officer"). It is the responsibility of the responding officer to determine whether there is any indication that the offender was motivated by bias. If a bias indicator is identified, the officer designates the incident as a "suspected bias-motivated crime" and forwards the case file to a "second-level judgment officer/unit." (In smaller agencies this is usually a person specially trained in hate crime matters, while in larger agencies it may be a special unit.) It is the task of the second-level judgment officer/unit to review the facts of the incident and make the final determination of whether a hate crime has actually occurred. If so, the incident is to be reported to the FBI UCR Program as a bias-motivated crime." (FBI, 2015, pp. 2-3)

As indicated, all decisions by the responding officer will be passed on for review to a second examiner. The FBI manual also outlines criteria that have to be full-filled for a crime to be classified as a hate crime:

> "An important distinction must be made when reporting a hate crime. The mere fact the offender is biased against the victim's actual or perceived race, religion, disability, sexual orientation, ethnicity, gender, and/or gender identity does not mean that a hate crime was involved. Rather, the offender's criminal act must have been motivated, in whole or in part, by his or her bias. Motivation is subjective, therefore, it is difficult to know with certainty whether a crime was the result of the offender's bias. For that reason, before an incident can be reported as a hate crime, sufficient objective facts must be present to lead a reasonable and prudent person to conclude that the offender's actions were motivated, in whole or in part, by bias. While no single fact may be conclusive, facts such as the following, particularly when combined, are supportive of a finding of bias:
>
> 1) The offender and the victim were of a different race, religion, disability, sexual orientation, ethnicity, gender, and/or gender identity. For example, the victim was African American and the offender was white.

2) Bias-related oral comments, written statements, or gestures were made by the offender indicating his or her bias. For example, the offender shouted a racial epithet at the victim.
3) Bias-related drawings, markings, symbols, or graffiti were left at the crime scene. For example, a swastika was painted on the door of a synagogue, mosque, or LGBT center.
4) Certain objects, items, or things which indicate bias were used. For example, the offenders wore white sheets with hoods covering their faces or a burning cross was left in front of the victim's residence.
5) The victim is a member of a specific group that is overwhelmingly outnumbered by other residents in the neighborhood where the victim lives and the incident took place.
6) The victim was visiting a neighborhood where previous hate crimes had been committed because of race, religion, disability, sexual orientation, ethnicity, gender, or gender identity and where tensions remained high against the victim's group.
7) Several incidents occurred in the same locality, at or about the same time, and the victims were all of the same race, religion, disability, sexual orientation, ethnicity, gender, or gender identity.
8) A substantial portion of the community where the crime occurred perceived that the incident was motivated by bias.
9) The victim was engaged in activities related to his or her race, religion, disability, sexual orientation, ethnicity, gender, or gender identity. For example, the victim was a member of the National Association for the Advancement of Colored People (NAACP) or participated in an LGBT pride celebration.
10) The incident coincided with a holiday or a date of significance relating to a particular race, religion, disability, sexual orientation, ethnicity, gender, or gender identity, e.g., Martin Luther King Day, Rosh Hashanah, or the Transgender Day of Remembrance.
11) The offender was previously involved in a similar hate crime or is a hate group member.
12) There were indications that a hate group was involved. For example, a hate group claimed responsibility for the crime or was active in the neighborhood.
13) A historically-established animosity existed between the victim's and the offender's groups.
14) The victim, although not a member of the targeted racial, religious, disability, sexual orientation, ethnicity, gender, or gender identity

> group, was a member of an advocacy group supporting the victim group."

(FBI, 2015, pp. 6-7)

We report the full list of FBI bias motivation categories in Table A.4. The hate crime categories we use in the paper are defined as follows:

**Table A.3—: FBI Hate Crimes Codes**

| **Hate Crime Category** | **FBI Codes** |
|---|---|
| Muslim | 24 |
| Hispanic | 32 |
| Other ethnic | 33 |
| Racial | 11, 12, 13, 14, 15, 16 |
| Sexual orientation | 41, 42, 43, 44, 45 |
| Religious (excluding Muslim) | 21, 22, 23, 25, 26, 27, 28, 29, 81, 82, 83, 84, 85 |

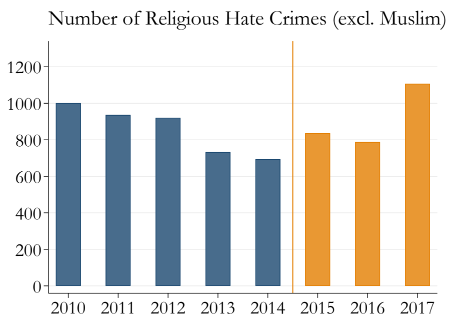
**Table A.4—: Full List of FBI Bias Motivation Categories**

| Bias category | Bias motivation and code |
|---|---|
| **Race/Ethnicity/Ancestry** | Anti-American Indian or Alaska Native (13)<br>Anti-Arab (31)<br>Anti-Asian (14)<br>Anti-Black or African American (12)<br>Anti-Hispanic or Latino (32)<br>Anti-Multiple Races, Group (15)<br>Anti-Native Hawaiian or Other Pacific Islander (16)<br>Anti-Other Race/Ethnicity/Ancestry (33)<br>Anti-White (11) |
| **Religion** | Anti-Buddhist (83)<br>Anti-Catholic (22)<br>Anti-Eastern Orthodox (81)<br>Anti-Hindu (84)<br>Anti-Islamic (Muslim) (24)<br>Anti-Jehovah's Witness (29)<br>Anti-Jewish (21)<br>Anti-Mormon (28)<br>Anti-Multiple Religions, Group (26)<br>Anti-Other Christian (82)<br>Anti-Other Religion (25)<br>Anti-Protestant (23)<br>Anti-Sikh (85)<br>Anti-Atheism/Agnosticism (27) |
| **Sexual Orientation** | Anti-Bisexual (45)<br>Anti-Gay (Male) (41)<br>Anti-Heterosexual (44)<br>Anti-Lesbian (42)<br>Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group) |
| **Disability** | Anti-Mental Disability (52)<br>Anti-Physical Disability (51) |
| **Gender** | Anti-Female (62)<br>Anti-Male (61) |
| **Gender Identity** | Anti-Gender Nonconforming (72)<br>Anti-Transgender (71) |

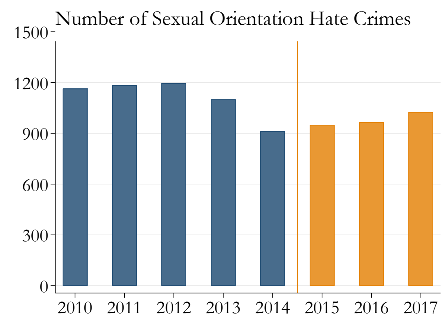
*Notes:* This table reports the complete list of hate crime bias motivations as classified by the FBI. The table is reproduced from (FBI, 2015, p. 5).

**Figure A.1. : Number of Hate Crimes, by Year and Motivating Bias**

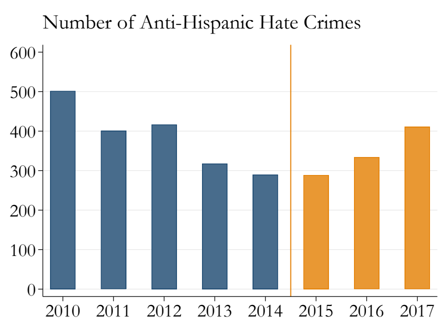
**(a) Religious bias (excl. Muslims)**



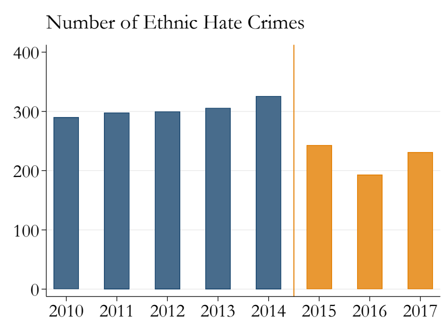

**(b) Sexual orientation bias**



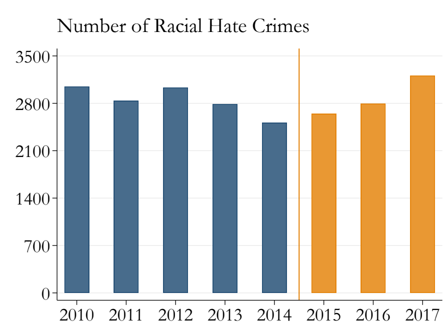

**(c) Anti-Hispanic bias**




**(d) Other ethnic bias**



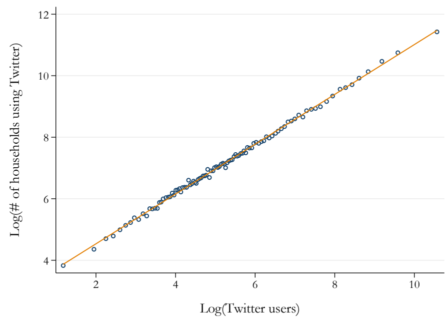

**(e) Racial bias**




*Notes:* These figures plot the number of yearly hate crimes, by year and type of hate crime (as defined by the FBI). The whiskers indicate 95% confidence intervals.

### *A.2. Geocoded Twitter Data*

**Figure A.2. : GESIS Twitter usage vs GfK Twitter usage**




*Notes:* This figure plots the county-level log number of Twitter users based on the Gesis data against the log number of Twitter users based on the data from GfK Mediamark Research & Intelligence.

**Table A.5—: Search Terms Used to Identify Users Tweeting about Other Festivals**

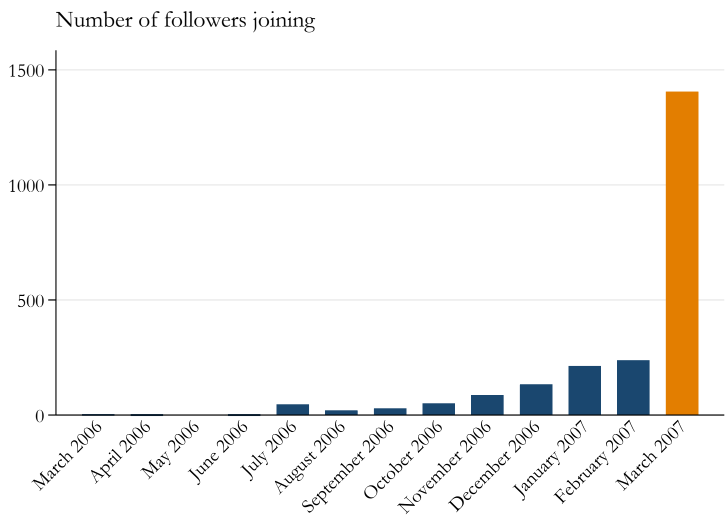
| Festival | Search Term |
|---|---|
| **South by Southwest Festival** | South by Southwest<br>SXSW |
| **Burning Man** | Burningman<br>Burning Man |
| **Coachella** | Coachella |
| **Lollapalooza** | Lollapalooza |
| **Pitchfork Music Festival** | Pitchfork Music Festival<br>Pitchforkfest |
| **Austin City Limited Festival** | Austin City Limits Festival |
| **Electric Daisy Carnival** | EDC Las Vegas<br>Electric Daisy Carnival |
| **New Orleans Jazz and Heritage Festival** | New Orleans Jazz and Heritage Festival<br>Jazzfest |

**Table A.6—: Search Terms Used to Create a Proxy for Total Tweets**

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | I | but | from | his | look | one | she | these | way | would |
| 1 | about | by | get | how | make | only | so | they | we | year |
| 2 | after | can | give | if | me | or | some | think | well | you |
| 3 | all | come | go | in | most | other | take | this | what | your |
| 4 | also | could | good | into | my | our | than | time | when | |
| 5 | any | day | have | it | new | out | that | two | which | |
| 6 | as | do | he | its | no | over | their | up | who | |
| 7 | at | even | he | just | not | people | them | us | with | |
| 8 | back | first | her | know | now | say | then | use | with | |
| 9 | because | for | him | like | on | see | there | want | work | |

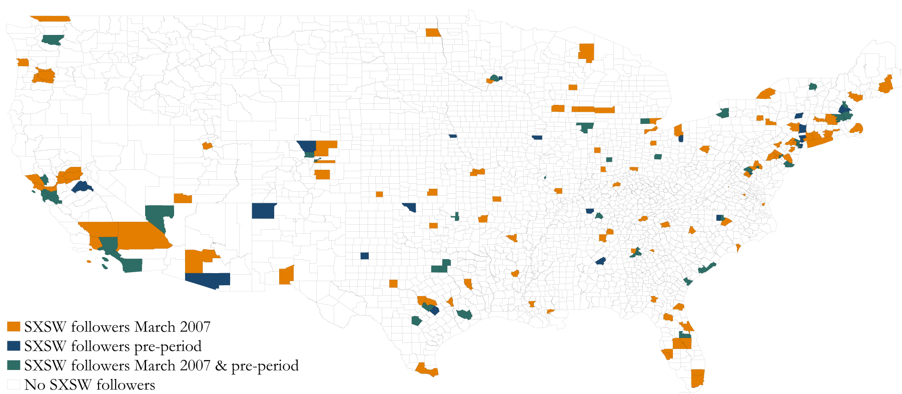
*Notes:* This table list the search terms we used to collect a proxy of all tweets sent from a given county.

**Figure A.3. : Number of SXSW Followers Joining Each Month**




*Notes:* This figure plots the number of SXSW followers who joined Twitter each month in the run-up to the 2007 SXSW festival. The orange bar marks the instrument used in the paper.

**Figure A.4. : Identifying Variation**




*Notes:* This map plots counties with SXSW followers who joined Twitter in March 2007 in orange; counties with SXSW followers who joined prior to the 2007 event in blue; and counties in both categories in green.

### A.3. Trump Twitter Data

## Table A.7—: Examples of Trump's Negative Tweets about Muslims

| Date | Text | Retweets |
|---|---|---|
| 12/10/2015 | "mimi_saulino: seanhannity @FoxNews Syrian Muslims escorted into U.S. through Mexico. Now arriving to Oklahoma and Kansas! Congress?" | 1223 |
| 14/11/2015 | Why won't President Obama use the term Islamic Terrorism? Isn't it now, after all of this time and so much death, about time! | 6924 |
| 15/11/2015 | "thewatcher23579: One of Paris terrorist came as Syrian refugee. Donald Trump is right again. BOMB THEIR OIL - TAKE AWAY THEIR FUNDING" | 2165 |
| 17/11/2015 | Refugees from Syria are now pouring into our great country. Who knows who they are - some could be ISIS. Is our president insane? | 16285 |
| 22/11/2015 | We better get tough with RADICAL ISLAMIC TERRORISTS, and get tough now, or the life and safety of our wonderful country will be in jeopardy! | 5172 |
| 25/11/2015 | I LIVE IN NEW JERSEY; @realDonaldTrump IS RIGHT: MUSLIMS DID CELEBRATE ON 9/11 HERE! WE SAW IT! https://t.co/1SksZU9qlj | 2252 |
| 07/12/2015 | Obama said in his speech that Muslims are our sports heroes. What sport is he talking about, and who? Is Obama profiling? | 9600 |
| 07/12/2015 | Statement on Preventing Muslim Immigration: https://t.co/HCWU16z6SR https://t.co/d1dhaIs0S7 | 4716 |
| 10/12/2015 | The United Kingdom is trying hard to disguise their massive Muslim problem. Everybody is wise to what is happening, very sad! Be honest. | 6028 |
| 10/12/2015 | In Britain, more Muslims join ISIS than join the British army. https://t.co/LQVNz7b2Eb | 4325 |
| 17/01/2016 | Far more killed than anticipated in radical Islamic terror attack yesterday. Get tough and smart U.S., or we won't have a country anymore! | 4126 |
| 27/03/2016 | Another radical Islamic attack, this time in Pakistan, targeting Christian women & children. At least 67 dead,400 injured. I alone can solve | 11353 |
| 22/05/2016 | Crooked Hillary wants a radical 500% increase in Syrian refugees. We can't allow this. Time to get smart and protect America! | 9758 |
| 12/06/2016 | Appreciate the congrats for being right on radical Islamic terrorism, I don't want congrats, I want toughness & vigilance. We must be smart! | 27146 |
| 13/06/2016 | In my speech on protecting America I spoke about a temporary ban, which includes suspending immigration from nations tied to Islamic terror. | 13026 |
| 25/06/2016 | We must suspend immigration from regions linked with terrorism until a proven vetting method is in place. | 11726 |
| 28/07/2016 | Hillary's refusal to mention Radical Islam, as she pushes a 550% increase in refugees, is more proof that she is unfit to lead the country. | 20106 |
| 18/10/2016 | Thank you Colorado Springs. If I'm elected President I am going to keep Radical Islamic Terrorists out of our count... https://t.co/N74UK73RLK | 12904 |
| 19/10/2016 | ISIS has infiltrated countries all over Europe by posing as refugees, and @HillaryClinton will allow it to happen h... https://t.co/MmeW2qsTQh | 16130 |
| 11/02/2017 | Our legal system is broken! "77% of refugees allowed into U.S. since travel reprieve hail from seven suspect countries." (WT) SO DANGEROUS! | 23082 |
| 17/08/2017 | Study what General Pershing of the United States did to terrorists when caught. There was no more Radical Islamic Terror for 35 years! | 30534 |
| 18/08/2017 | Radical Islamic Terrorism must be stopped by whatever means necessary! The courts must give us back our protective rights. Have to be tough! | 37669 |
| 15/09/2017 | Loser terrorists must be dealt with in a much tougher manner.The internet is their main recruitment tool which we must cut off & use better! | 21411 |
| 20/10/2017 | Just out report: "United Kingdom crime rises 13% annually amid spread of Radical Islamic terror." Not good, we must keep America safe! | 29854 |
| 01/11/2017 | NYC terrorist was happy as he asked to hang ISIS flag in his hospital room. He killed 8 people, badly injured 12. SHOULD GET DEATH PENALTY! | 43455 |

*Notes:* This table reports examples of Trump's negative tweets about Muslims, including the date of the tweet and the number of retweets the tweet received.

## Table A.8—: Misclassified Trump's Anti-Muslim Tweets

| Date | Text | Retweets |
|---|---|---|
| 12/12/2012 | Watching Pyongyang terrorize Asia today is just amazing! | 77 |
| 26/03/2013 | The Scottish windfarm was conceived by the same mind that released terrorist al-Megrahi for humanitarian reasons. .. | 101 |
| 23/04/2013 | Did the Boston terrorists register their guns? No. Another example of why gun control legislation is not the answer! | 1192 |
| 22/09/2013 | "@LebaneseKobe: @realDonaldTrump as a Muslim and as an American, i know for a fact that you Mr. Trump respect all people! | 33 |
| 22/09/2013 | "@mandem3: realDonaldTrump you hate muslims." Wrong | 48 |
| 10/10/2013 | Obama has called @GOP terrorists during this showdown. It's a shame he really doesn't think it because then he would meet all @GOP demands. | 432 |
| 29/01/2014 | Remember when "comedian" Bill Maher openly praised the disgusting terrorists who destroyed the World Trade Center-then got canned by ABC? | 117 |
| 26/01/2015 | "tomtumillo: What is worse, Geraldo screaming 'screw the terrorists' or Kenya feeling she's 'fabulous'? #CelebrityApprentice | 56 |
| 15/08/2015 | "javonniandjeno: realDonaldTrump AP nbc Donald Trump is Clint Eastwood, the perfect hero not scared of American terrorists. Vote Trump!" | 1742 |
| 27/08/2015 | "jp_sitles: realDonaldTrump HillaryClinton: she compared republicans to terrorist but will not call terrorists , terrorists. #OhMe" | 2869 |
| 06/09/2015 | "jasonusmc2017: blayne_troy @realDonaldTrump: He was right when he called Obama the 5 for 1 president. 5 terrorist for one no good traitor | 1016 |
| 21/09/2015 | "TheBrodyFile: On the Muslim issue: It might help @BarackObama if he actually supported Christians religious liberty rights. | 1242 |
| 21/09/2015 | "TheBrodyFile: On the Muslim issue: It might help @BarackObama if he didn't take five years to visit Israel" | 818 |
| 21/11/2015 | "WayneDupreeShow: "It's clear that Donald Trump was NOT even talking about a Muslim Database!" https://t.co/3tLDZj2WGV" | 1020 |
| 31/12/2015 | "SenSanders: I have a message for Donald Trump: No, we're not going to hate Latinos, we're not going to hate Muslims." I fully agree! | 1250 |
| 23/03/2016 | Just watched Hillary deliver a prepackaged speech on terror. She's been in office fighting terror for 20 years- and look where we are! | 11115 |
| 23/03/2016 | I will be the best by far in fighting terror. I'm the only one that was right from the beginning, & now Lyin' Ted & others are copying me. | 7224 |
| 15/06/2016 | I will be meeting with the NRA, who has endorsed me, about not allowing people on the terrorist watch list, or the no fly list, to buy guns. | 13903 |
| 21/05/2017 | Speech transcript at Arab Islamic American Summit https://t.co/eUWxJXJxbe nReplay https://t.co/VtmlSqciXx #RiyadhSummit #POTUSAbroad | 11498 |
| 26/05/2017 | Getting ready to engage G7 leaders on many issues including economic growth, terrorism, and security. | 11322 |
| 27/05/2017 | Big G7 meetings today. Lots of very important matters under discussion. First on the list, of course, is terrorism. #G7Taormina | 9489 |
| 18/08/2017 | Today, I signed the Global War on Terrorism War Memorial Act (#HR873.) The bill authorizes....cont https://t.co/c3zIkdtowc https://t.co/re6n0MS0cj | 14892 |
| 07/09/2017 | During my trip to Saudi Arabia, I spoke to the leaders of more than 50 Arab & Muslim nations about the need to confront our shared enemies.[...] | 10156 |
| 11/11/2017 | When will all the haters and fools out there realize that having a good relationship with Russia is a good thing, not a bad thing.[...] | 39627 |

*Notes:* The table lists the tweets we excluded by hand from the set of negative Muslim tweets that were identified by the machine learning model. See text for details.

### *A.4. Rescaling of Google trends*

As described in Section I, we use weekly Google trends data to rescale daily values. The daily Google trends data are scaled between 0-100 for each 90 day period, while the weekly Google trends data have a consistent scaling for the entire time period.

To arrive at consistent values, we use the following process. First, we create a scaling factor by dividing the weekly interest by 100. We then multiply the daily data with the scaling factor. If the weekly interest is 100, the scaling factor would be 1, and the daily values would remain the same. On the other hand, if the weekly interest is low, say 10, the daily interest would be scaled down. This way, the adjustment guarantees that daily search interest is on the same scale and thus comparable over time.

As a final step, we divide the rescaled values by their maximum and multiply them by 100. This is to re-normalize the Google trend values to take on values between 0 and 100.

### *A.5. Sources for Trump's golf activity*

**Table A.9—: Sources for Golf Data**

| Source | Description |
|---|---|
| New York Times | The NYT tracks visits by Trump to his own properties. The data also track how often Trump visited a golf club. |
| trumpgolfcount.com | This website lists Trump's visits to golf clubs since his inauguration. It also provides additional analysis during which visits Trump likely played golf. |
| Presidential Schedule | The presidential schedule lists all past presidential journeys. |

### *A.6. Calculating the Similarity of SXSW Followers and All Twitter Users*

We calculate the similarity of all Twitter user profiles to those of SXSW followers using Latent Semantic Analysis (LSA) (Deerwester et al., 1990; Landauer, 2007). While we could create a similarity measure based on the word count in the Twitter profile bios, this measure would be less reliable at the individual-level as the bio strings are very short and the resulting document-word matrix therefore extremely sparse.

LSA improves on such a measure by reducing the dimensions of the document-word matrix using singular value decomposition. Singular value decomposition derives the components that best describe the semantic space and as a result even profile bios that do not have a single word in common can be similar if they contain words that are used in similar context (e.g. website and webpage).

**Table A.10—: Summary Statistics by Day of Week (2017 only)**

| **Day of week** | | **Hate crimes against Muslims** | **Tweets about Muslims** | **Trump golfs** |
|---|---|---|---|---|
| Monday | Sum | 43 | 3 | 4 |
| | Mean | 0.83 | 0.06 | 0.08 |
| Tuesday | Sum | 33 | 6 | 3 |
| | Mean | 0.63 | 0.12 | 0.06 |
| Wednesday | Sum | 43 | 10 | 4 |
| | Mean | 0.83 | 0.19 | 0.08 |
| Thursday | Sum | 43 | 6 | 6 |
| | Mean | 0.83 | 0.12 | 0.12 |
| Friday | Sum | 36 | 12 | 13 |
| | Mean | 0.69 | 0.23 | 0.25 |
| Saturday | Sum | 36 | 4 | 30 |
| | Mean | 0.69 | 0.08 | 0.58 |
| Sunday | Sum | 42 | 6 | 32 |
| | Mean | 0.79 | 0.11 | 0.60 |
| **Total** | Sum | 276 | 47 | 92 |
| | Mean | 0.76 | 0.13 | 0.25 |

*Notes:* This table presents descriptive statistics by day of week for the number of anti-Muslim hate crimes, the number of Trump's tweets about Muslims and the number of Trump's golf outing for the sample used in the instrumental variable regressions (2017 only).

See Iaria, Schwarz and Waldinger (2018) for an example using a similar approach. For a more extensive description of LSA as well as a Stata implementation see Landauer (2007) and Schwarz (2019).

In our setting, we prepare the data by removing stopwords and reducing all words to their morphological routs, so called lemmas. We then extract all words that appear in at least 5 Twitter bios. This allows us to construct a word-document matrix which is then reweighted using term-frequency inverse document frequency. Afterwards, we use LSA to extract the first 300 principle components of the matrix. The resulting matrix is then used to calculate the cosine similarity between the biography strings of each user in the Kinder-Kurlanda et al. (2017) data with each follower of the SXSW festival. We then normalize the similarity measure to have mean 0 and standard deviation 1 to facilitate the interpretation.

**Table A.11—: Variable Descriptions (Part 1/3)**

| Variable | Description | Source |
|---|---|---|
| **Hate crime variables** | | |
| Hate crimes | Total number of hate crimes recorded in the FBI hate crime data. | FBI Hate Crime Data |
| Anti-Muslim hate crimes | Anti-Muslim hate crimes recorded in the FBI hate crime data, based on bias motivation code 24. | FBI Hate Crime Data |
| Anti-Hispanic hate crimes | Anti-Hispanic hate crimes recorded in the FBI hate crime data, based on the bias motivation codes 32. | FBI Hate Crime Data |
| Other ethnic-based hate crimes | Anti-ethnic hate crimes recorded in the FBI hate crime data, based on the bias motivation codes 33. | FBI Hate Crime Data |
| Anti-racial hate crimes | Racial hate crimes recorded in the FBI hate crime data, based on bias motivation codes 11, 12, 13, 14, 15, 16. | FBI Hate Crime Data |
| Anti-religious hate crimes | Anti-religious hate crimes (except anti-Muslim) recorded in the FBI hate crime data, based on bias motivation codes 21, 22, 23, 25, 26, 27, 28, 29, 81, 82, 83, 84, 85. | FBI Hate Crime Data |
| Anti-sexual orientation hate crimes | Hate crimes based on sexual orientation recorded in the FBI hate crime data, based on the bias motivation codes 41, 42, 43, 44, 45. | FBI Hate Crime Data |
| **Twitter data** | | |
| Trump tweets | The total number of tweets from Donald Trump's Twitter account. | Trump Twitter Archive |
| Muslim tweets | The number of tweets from Donald Trump's Twitter account about Islam-related topics. We start classifying these tweets by searching for the terms "sharia", "refugee", "mosque", "muslim", "islam" and "terror". We then read all tweets and verify that they indeed mention Muslims in a negative way. | Trump Twitter Archive |
| Twitter usage | The number of geolocated tweets per county that were collected using the Twitter streaming API in a 12 month period from June to November 2014 and June to November 2015. | Gesis Datatorium |
| SXSW followers, March 2007 | The number of Twitter users following the SXSW account in each county that signed up to Twitter in March 2007. | Twitter Search API |
| SXSW followers, Pre | The total number of Twitter users following the SXSW account in each county that signed up to Twitter at any point in 2006. | Twitter Search API |
| Burning Man Twitter Users, August 2007 | The number of Twitter users in each county that tweeted about the Burning Man festival in August 2007 and joined Twitter in August 2007. | Twitter Search API |
| Coachella Twitter Users, April 2007 | The number of Twitter users in each county that tweeted about the Coachella festival in April 2007 and joined Twitter in April 2007. | Twitter Search API |
| Lollapalooza Twitter Users, August 2007 | The number of Twitter users in each county that tweeted about the Lollapalooza festival in August 2007 and joined Twitter in August 2007. | Twitter Search API |

**Table A.11—: Variable Descriptions (Part 2/3)**

| Variable | Description | Source |
|---|---|---|
| | **Other cross-sectional controls** | |
| Demographic controls | Contain the share of people in the age buckets 20-24, 25-29, 30-34, 40-44, 45-49 and 50+, and the percentage change in population between 2000 and 2016. | US Census |
| Geographical controls | Contains the distance to Austin Texas, population density, and the logarithm of the land area for each county. | US Census Tigerline File (United States Census Bureau, 2021b) |
| Race and religion controls | Contains population shares of Muslims, Whites, Blacks, Native Americans, Asians, and Hispanics. | US Census/Religious Census |
| Socioeconomic controls | Contains the share of people over 25 with at least a high school degree and the share of people over 25 with at least a graduate degree, a county's poverty rate, unemployment rate, GINI coefficient, share of uninsured, log of median household income, and the share of the population employed in agriculture, manufacturing, accommodation/retail, utilities, information technologies services, and other industries. | US Census/Bureau of Labor Statistics |
| Media controls | Contains the ratio of prime time TV viewership to population, cable spending to population, and the share of Fox News viewership. | SimplyAnalytics |
| Election control | Contains the vote share of the Republican party in the 2012 presidential election. | MIT Election Lab |
| Crime controls | Contains the number of violent crime per capita as well as the number of property crimes per capita based on FBI data. | FBI UCR Data |

**Table A.11—: Variable Descriptions (Part 3/3)**

| Variable | Description | Source |
|---|---|---|
| **Trump golf data** | | |
| Trump golfs | A dummy variable for each day in 2017 Trump spent on a golf course and likely played golf. | NYT, trumpgolfcount.com and Pres. Schedule |
| Trump golfs (NYT only) | A dummy variable for each day in 2017 Trump spent on a Golf course and likely golfed, based solely on the information of the New York Times. | NYT |
| Trump golf (alternative) | A dummy variable for each day in 2017 Trump spent on a golf course and likely golfed, based on the information of trumpgolfcount.com and extended with information from the Pres. Schedule | trumpgolfcount.com and Pres. Schedule |
| Golf holiday | A dummy for any of Trump's golf outings that lasts longer than 3 days. | NYT and trumpgolfcount.com |
| Golf at any point in previous week | A dummy variable which is 1 if Trump golfed at any point in the previous week. | NYT and trumpgolfcount.com |
| **Other time series variables** | | |
| Trump followers' retweets | The number of retweets of Trump's tweets about Muslims by his Twitter followers | Twitter |
| Trump followers' new content | The number of tweets by Trump followers containing the words "sharia", "refugee", "mosque", "muslim", "islam" or "terror". | Twitter |
| #StopIslam or #BanIslam | The number of tweets by Trump followers containing the terms "#StopIslam" or "#BanIslam". | Twitter |
| Muslim mentions (total) | The total number of cable news reports mentioning one of the following terms in their closed captions: "sharia", "refugee", "mosque", "muslim", "islam" and "terror". | Internet Archive |
| Muslim mentions (Fox News) | The total number of news reports on Fox News mentioning one of the following terms in their closed captions: "sharia", "refugee", "mosque", "muslim", "islam" and "terror". | Internet Archive |
| Muslim mentions (CNN) | The total number of news reports on CNN mentioning one of the following terms in their closed captions: "sharia", "refugee", "mosque", "muslim", "islam" and "terror". | Internet Archive |
| Muslim mentions (MSNBC) | The total number of news reports on MSNBC mentioning one of the following terms in their closed captions: "sharia", "refugee", "mosque", "muslim", "islam" and "terror". | Internet Archive |
| Google searches (PC) | The first princepal component of the rescaled Google trends for the following terms: "sharia", "refugee", "mosque", "muslim", "islam" and "terror". | Google Trends |
| Terror attack in the US and Europe | The number of Islamist terror attacks committed in the US. | Global Terrorism Database |

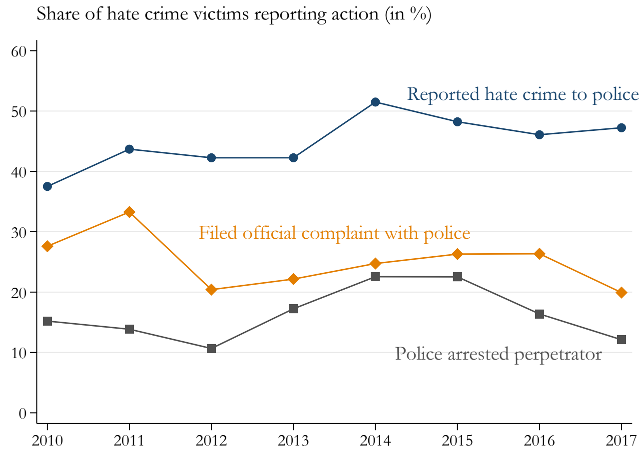
## Appendix 2: Additional Cross-Sectional Evidence

**Table A.12—: Social Media and Hate Crimes - Split by Number of Perpetrators**

| | Muslim bias | | Hispanic bias | |
|---|---|---|---|---|
| | One offender | Multiple offenders | One offender | Multiple offenders |
| | (1) | (2) | (3) | (4) |
| **Panel A: OLS** | | | | |
| Log(Twitter users) | 0.020*** | 0.004 | 0.001 | -0.005 |
| | (0.005) | (0.005) | (0.008) | (0.006) |
| **Panel B: Reduced form** | | | | |
| Log(SXSW followers, March 2007) | 0.033 | 0.026* | 0.063** | 0.002 |
| | (0.026) | (0.015) | (0.025) | (0.021) |
| **Panel C: 2SLS** | | | | |
| Log(Twitter users) | 0.068 | 0.053 | 0.131** | 0.004 |
| | (0.053) | (0.032) | (0.049) | (0.042) |
| Weak IV 95% AR confidence set | [-0.030; 0.167] | [-0.006; 0.120] | [0.039; 0.222] | [-0.082; 0.074] |
| Log(SXSW followers, Pre) | 0.037 | -0.009 | -0.049 | -0.005 |
| | (0.058) | (0.034) | (0.055) | (0.039) |
| Observations | 3,106 | 3,106 | 3,106 | 3,106 |
| Mean of DV | 0.013 | 0.003 | -0.005 | -0.002 |
| Robust F-stat. | 76.58 | 76.58 | 76.58 | 76.58 |
| Share of hate crimes | 81% | 19% | 78% | 22% |

*Notes:* This table presents county-level OLS and IV regressions where the dependent variable is the log change in hate crimes with the indicated number of offenders between 2010 and 2017. We have information on the number of perpetrators for 62% of hate crimes in our sample. The bottom row reports the percentage of hate crimes falling into the one and multiple offender categories for incidents for which we have information. *Log(Twitter usage)* is instrumented using the number of users who started following SXSW in March 2007. *SXSW followers, Pre* is the number of SXSW followers who registered at some point in 2006. All regressions control for population deciles and state fixed effects (not shown). We also control the full set of controls. For the just-identified case we study here, the "robust" $F$-stat. is equivalent to the "Kleibergen-Paap" or the "effective" $F$-statistic of Olea and Pflueger (2013). Standard errors are clustered by state. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Figure A.5. : Trends in Hate Crime Reporting**




*Notes:* This figure visualizes time series trends in the reporting of hate crimes and police actions taken in response to them. The source is the Bureau of Justice Statistics National Crime Victimization Survey (NCVS). The sample consists of 1,416 hate crime incidents reported between 2010 and 2017. We report the share of respondents that took each action using victimization weights.

**Table A.13—: Placebo - Social Media and Changes in Property Crimes Reported by the FBI**

| | ΔLog(Property crimes) | | | | |
|---|---|---|---|---|---|
| | Property (1) | Robbery (2) | Burglary (3) | Larceny (4) | Car theft (5) |
| **Panel A: Reduced form** | | | | | |
| Log(SXSW followers, March 2007) | -0.038 | 0.000 | -0.039 | -0.030 | -0.029 |
| | (0.029) | (0.027) | (0.033) | (0.030) | (0.028) |
| **Panel B: 2SLS** | | | | | |
| Log(Twitter users) | -0.080 | 0.001 | -0.081 | -0.063 | -0.060 |
| | (0.061) | (0.057) | (0.068) | (0.064) | (0.057) |
| Weak IV 95% AR confidence set | [-0.193; 0.033] | [-0.104; 0.116] | [-0.206; 0.045] | [-0.194; 0.055] | [-0.165; 0.045] |
| Log(SXSW followers, Pre) | -0.054 | -0.035 | -0.051 | -0.049 | -0.098** |
| | (0.039) | (0.046) | (0.048) | (0.042) | (0.043) |
| Observations | 3,106 | 3,106 | 3,106 | 3,106 | 3,106 |
| Mean of DV | -0.143 | -0.030 | -0.234 | -0.128 | 0.057 |
| Robust F-stat. | 72.64 | 72.64 | 72.64 | 72.64 | 72.64 |

*Notes:* This table presents county-level reduced-form and IV regressions where the dependent variable is the log change in property crimes of different types reported by the FBI between 2010 and 2016. More specifically, we take the difference between the number of crimes in 2016 (in logs) and the average number of crimes between 2010 and 2014 (in logs); data for 2015 and 2017 were not available from the ICPSR FBI UCR repository. *Log(Twitter usage)* is instrumented using the number of users who started following SXSW in March 2007. *SXSW followers, Pre* is the number of SXSW followers who registered at some point in 2006. All regressions control for population deciles and state fixed effects (not shown). Demographic controls include population growth between 2000 and 2016 as well as age cohort controls for the share of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, and those over 50. Race and religion controls contains the share of people identifying as white, African American, Native American or Pacific Islander, Asian, Hispanic, or Muslim. Socioeconomic controls include the poverty rate, unemployment rate, local GINI index, the share of uninsured individuals, log median household income, the share of high school graduates, the share of people with a graduate degree, as well as the employment shares in agriculture, information technology, manufacturing, nontradables, construction and real estate, utilities, business services, or other sectors. Media controls include the viewership share of Fox News, the cable TV spending to population ratio, and the prime time TV viewership to population ratio. Election control is the county-level vote share of the Republican party in 2012. Crime controls are the rates of violent or property crime from the FBI. Geographical controls include the linear distance from the SXSW festival location (Austin, Texas), population density, and the natural logarithm of county size. Weak IV 95% Anderson-Rubin (AR) confidence sets are calculated using the two-step approach of Andrews (2018) using the Stata package from Sun (2018). For the just-identified case we study here, the "robust" $F$-stat. is equivalent to the "Kleibergen-Paap" or the "effective" $F$-statistic of Olea and Pflueger (2013). Robust standard errors in parentheses are clustered by state. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.14—: Social Media and Hate Crimes - Alternative Standard Errors**

| | Robust SE (1) | Bootstrap robust SE (2) | Bootstrap state cluster SE (3) | Spatial SE (4) |
|---|---|---|---|---|
| **Panel A: OLS** | | | | |
| Log(Twitter users) | 0.029*** | 0.029*** | 0.029*** | 0.029*** |
| | (0.007) | (0.007) | (0.009) | (0.008) |
| **Panel B: Reduced form** | | | | |
| Log(SXSW followers, March 2007) | 0.069** | 0.069*** | 0.069** | 0.069** |
| | (0.027) | (0.026) | (0.032) | (0.030) |
| **Panel C: 2SLS** | | | | |
| Log(Twitter users) | 0.118** | 0.118** | 0.118** | 0.118** |
| | (0.048) | (0.047) | (0.051) | (0.053) |
| Log(SXSW followers, Pre) | 0.013 | 0.013 | 0.013 | 0.013 |
| | (0.054) | (0.059) | (0.062) | (0.068) |
| Observations | 3,107 | 3,107 | 3,107 | 3,107 |
| Mean of DV | 0.019 | 0.019 | 0.019 | 0.019 |
| Robust F-stat. | 68.42 | 68.42 | 85.52 | 71.61 |

*Notes:* This table presents county-level OLS and IV regressions where the dependent variable is the log change in hate crimes against Muslims between 2010 and 2017. *Log(Twitter usage)* is instrumented using the number of users who started following SXSW in March 2007. *SXSW followers, Pre* is the number of SXSW followers who registered at some point in 2006. All regressions control for population deciles and state fixed effects (not shown). Demographic controls include population growth between 2000 and 2016 as well as age cohort controls for the share of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, and those over 50. Spatial standard errors are based on the method proposed in Colella et al. (2019), implemented in Stata as *acreg*, using a 200 miles cutoff. For the just-identified case we study here, the "robust" $F$-stat. is equivalent to the "Kleibergen-Paap" or the "effective" $F$-statistic of Olea and Pflueger (2013). Standard errors are computed as indicated in the top row. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.15—: Comparing Counties With SXSW Followers, March 2007 vs. Pre

| | March 2007 *and* Pre (1) | March 2007 *only* (2) | Pre *only* (3) | Difference in means (2) - (3) | p-value | Šidàk p-value |
|---|---|---|---|---|---|---|
| **Demographic controls** | | | | | | |
| % aged 20-24 | 0.07 | 0.08 | 0.08 | 0.00 | 0.92 | 1.00 |
| % aged 25-29 | 0.09 | 0.07 | 0.07 | -0.00 | 0.51 | 1.00 |
| % aged 30-34 | 0.08 | 0.07 | 0.07 | -0.00 | 0.58 | 1.00 |
| % aged 35-39 | 0.07 | 0.06 | 0.06 | -0.00 | 0.82 | 1.00 |
| % aged 40-44 | 0.06 | 0.06 | 0.06 | 0.00 | 0.82 | 1.00 |
| % aged 45-49 | 0.07 | 0.06 | 0.06 | 0.00 | 0.89 | 1.00 |
| % aged 50+ | 0.32 | 0.35 | 0.35 | -0.00 | 0.97 | 1.00 |
| Population growth, 2000-2016 | 0.18 | 0.18 | 0.15 | 0.03 | 0.56 | 1.00 |
| **Geographical controls** | | | | | | |
| Population density | 5192.27 | 1021.39 | 1998.35 | -976.96 | 0.07* | 0.93 |
| Log(County area) | 6.30 | 6.63 | 6.54 | 0.09 | 0.73 | 1.00 |
| Distance from Austin, TX (in miles) | 1775.99 | 1749.38 | 1626.64 | 122.74 | 0.48 | 1.00 |
| **Race and religion controls** | | | | | | |
| % white | 0.50 | 0.65 | 0.67 | -0.02 | 0.62 | 1.00 |
| % black | 0.18 | 0.12 | 0.08 | 0.04 | 0.20 | 1.00 |
| % native American | 0.01 | 0.01 | 0.02 | -0.02 | 0.02** | 0.49 |
| % Asian | 0.10 | 0.05 | 0.05 | -0.01 | 0.55 | 1.00 |
| % Hispanic | 0.20 | 0.16 | 0.15 | 0.01 | 0.80 | 1.00 |
| % Muslim | 0.01 | 0.01 | 0.01 | 0.00 | 0.87 | 1.00 |
| **Socioeconomic controls** | | | | | | |
| % below poverty level | 15.71 | 15.82 | 13.69 | 2.14 | 0.17 | 1.00 |
| % unemployed | 4.86 | 5.05 | 4.51 | 0.54 | 0.07* | 0.93 |
| Gini index | 0.48 | 0.46 | 0.45 | 0.01 | 0.24 | 1.00 |
| % uninsured | 12.87 | 12.40 | 11.21 | 1.19 | 0.35 | 1.00 |
| Log(Median household income) | 11.00 | 10.91 | 10.99 | -0.09 | 0.18 | 1.00 |
| % employed in agriculture | 0.00 | 0.00 | 0.00 | 0.00 | 0.27 | 1.00 |
| % employed in IT | 0.04 | 0.02 | 0.02 | -0.00 | 0.98 | 1.00 |
| % employed in manufacturing | 0.07 | 0.09 | 0.09 | 0.01 | 0.63 | 1.00 |
| % employed in nontradable sector | 0.23 | 0.26 | 0.27 | -0.01 | 0.52 | 1.00 |
| % employed in construction/real estate | 0.06 | 0.07 | 0.07 | 0.01 | 0.39 | 1.00 |
| % employed in utilities | 0.04 | 0.04 | 0.03 | 0.00 | 0.56 | 1.00 |
| % employed in business services | 0.29 | 0.25 | 0.24 | 0.01 | 0.70 | 1.00 |
| % employed in other services | 0.27 | 0.26 | 0.28 | -0.02 | 0.27 | 1.00 |
| % adults with high school degree | 21.76 | 25.99 | 25.77 | 0.22 | 0.88 | 1.00 |
| % adults with graduate degree | 16.15 | 13.08 | 14.34 | -1.26 | 0.40 | 1.00 |
| **Media controls** | | | | | | |
| % watching Fox News | 0.25 | 0.26 | 0.26 | -0.00 | 0.91 | 1.00 |
| % watching prime time TV | 0.42 | 0.43 | 0.43 | 0.00 | 0.91 | 1.00 |
| **Election control** | | | | | | |
| Republican vote share, 2012 | 0.33 | 0.46 | 0.47 | -0.02 | 0.63 | 1.00 |
| **Crime controls** | | | | | | |
| Violent crime rate | 0.01 | 0.00 | 0.00 | 0.00 | 0.98 | 1.00 |
| Property crime rate | 0.03 | 0.02 | 0.02 | 0.00 | 0.30 | 1.00 |

*Notes:* This table plots the mean values of the control variables for the three types of counties relevant for the cross-sectional results: (1) counties with new SXSW followers in March 2007 *and* the pre-period; (2) counties with new SXSW followers in March 2007 but no new followers in the pre-period; and (3) counties with new SXSW followers in the pre-period but no new followers in March 2007. We report p-values from a two-sided $t$-test for the equality of means between the counties with the key identifying variation, as well as Šidàk-corrected values to account for multiple hypothesis testing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.16—: Balancedness - SXSW Twitter Followers' Characteristics**

| **User first names (Corr. = 0.69)** | | **Terms used in user bios (Corr. = 0.92)** | |
|---|---|---|---|
| Pre-SXSW | March 2007 | Pre-SXSW | March 2007 |
| michael | michael | http | http |
| mike | john | founder | com |
| paul | chris | com | digital |
| chris | jeff | co | founder |
| ryan | matt | tech | medium |
| eric | brian | design | director |
| david | david | director | tech |
| matthew | alex | product | music |
| john | jason | digital | social |
| jeff | kevin | designer | marketing |
| robert | paul | medium | design |
| mark | mike | music | co |
| andrew | dan | social | writer |
| daniel | andrew | love | love |
| james | peter | marketing | lover |
| kevin | jim | web | dad |
| jay | tom | geek | creative |
| jonathan | jennifer | writer | tweet |
| rob | steve | technology | author |
| rachel | todd | dad | designer |

*Notes:* This table compares the individual characteristics of Twitter users who follow "South by Southwest", depending on the users' join date (either in March 2007 or before). We plot the ranking of the most common first names and terms used in a Twitter user's "bio".

**Table A.17—: Comparison of Followers in SXSW counties and All Twitter Users**

| User first names (Corr. = 0.97) | | Terms used in user bios (Corr. = 0.94) | |
|---|---|---|---|
| Other counties | SXSW counties | Other counties | SXSW counties |
| michael | michael | love | co |
| chris | david | life | love |
| john | chris | co | life |
| david | john | http | http |
| sarah | alex | http co | http co |
| mike | mike | god | music |
| emily | matt | ig | lover |
| ryan | sarah | music | ig |
| matt | ryan | university | de |
| alex | andrew | like | like |
| taylor | emily | fan | fan |
| ashley | brian | live | world |
| nick | jessica | lover | instagram |
| jessica | james | mom | thing |
| tyler | kevin | husband | la |
| hannah | daniel | time | live |
| katie | ashley | follow | time |
| amanda | jason | one | com |
| lauren | lauren | wife | artist |
| brian | mark | thing | one |

*Notes:* This table compares the individual characteristics of Twitter users from counties with "South by Southwest" followers who joined in March 2007 ("SXSW counties") to Twitter users from all other US counties ("Other counties"). We plot the ranking of the most common first names and terms used in a Twitter user's "bio".

**Table A.18—: Correlation of Log(Twitter Users) Across Events**

| | SXSW March 2007 | SXSW Pre | Coachella April 2007 | Burning Man August 2007 | Lollapalooza August 2007 |
|---|---|---|---|---|---|
| SXSW followers, March 2007 | 1 | | | | |
| SXSW followers, Pre | 0.77 | 1 | | | |
| Coachella followers, April 2007 | 0.62 | 0.62 | 1 | | |
| Burning Man followers, August 2007 | 0.66 | 0.68 | 0.48 | 1 | |
| Lollapalooza followers, August 2007 | 0.56 | 0.56 | 0.46 | 0.42 | 1 |

*Notes:* This table reports the Pearson correlation coefficients between the main measure of interest (*SXSW followers, March 2007*) and different control variables. "Followers" are based on the locations of people who started following SXSW or one of the other festivals in a given month. We take the natural logarithm of these numbers with one added inside.

## Table A.19—: Social Media and Types of Hate Crimes

| | Any (1) | Vandalism (2) | Theft (3) | Burglary (4) | Robbery (5) | Assault (6) |
|---|---|---|---|---|---|---|
| **Panel A: OLS** | | | | | | |
| Log(Twitter users) | 0.029*** | 0.047** | 0.002 | 0.009 | 0.004 | 0.079*** |
| | (0.008) | (0.021) | (0.003) | (0.007) | (0.007) | (0.018) |
| **Panel B: Reduced form** | | | | | | |
| Log(SXSW followers, March 2007) | 0.069** | 0.047 | 0.006 | 0.014 | 0.001 | 0.095** |
| | (0.030) | (0.030) | (0.007) | (0.015) | (0.004) | (0.040) |
| **Panel C: 2SLS** | | | | | | |
| Log(Twitter users) | 0.118** | 0.080 | 0.009 | 0.024 | 0.002 | 0.163** |
| | (0.052) | (0.051) | (0.012) | (0.024) | (0.007) | (0.064) |
| Weak IV 95% AR confidence set | [0.021; 0.225] | [-0.013; 0.172] | [-0.013; 0.035] | [-0.025; 0.068] | [-0.011; 0.014] | [0.045; 0.281] |
| Log(SXSW followers, Pre) | 0.013 | 0.066 | -0.004 | -0.023 | 0.017 | 0.011 |
| | (0.069) | (0.057) | (0.009) | (0.019) | (0.025) | (0.070) |
| Observations | 3,107 | 569 | 569 | 569 | 569 | 569 |
| Mean of DV | 0.019 | 0.038 | 0.002 | 0.002 | 0.004 | 0.067 |
| Robust F-stat. | 86.85 | 61.25 | 61.25 | 61.25 | 61.25 | 61.25 |

*Notes:* This table presents county-level OLS and IV regressions where the dependent variable is the log change in hate crimes against Muslims of the type in the top row between 2010 and 2017. *Log(Twitter usage)* is instrumented using the number of users who started following SXSW in March 2007. *SXSW followers, Pre* is the number of SXSW followers who registered at some point in 2006. All regressions control for population deciles and state fixed effects (not shown). Demographic controls include population growth between 2000 and 2016 as well as age cohort controls for the share of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, and those over 50. Race and religion controls contains the share of people identifying as white, African American, Native American or Pacific Islander, Asian, Hispanic, or Muslim. Socioeconomic controls include the poverty rate, unemployment rate, local GINI index, the share of uninsured individuals, log median household income, the share of high school graduates, the share of people with a graduate degree, as well as the employment shares in agriculture, information technology, manufacturing, nontradables, construction and real estate, utilities, business services, or other sectors. Media controls include the viewership share of Fox News, the cable TV spending to population ratio, and the prime time TV viewership to population ratio. Election control is the county-level vote share of the Republican party in 2012. Crime controls are the rates of violent or property crime from the FBI. Geographical controls include the linear distance from the SXSW festival location (Austin, Texas), population density, and the natural logarithm of county size. Weak IV 95% Anderson-Rubin (AR) confidence sets are calculated using the two-step approach of Andrews (2018) using the Stata package from Sun (2018). For the just-identified case we study here, the "robust" $F$-stat. is equivalent to the "Kleibergen-Paap" or the "effective" $F$-statistic of Olea and Pflueger (2013). Robust standard errors in parentheses are clustered by state. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.20—: Heterogeneous Effects - Hate Groups and Hate Crimes**

| Dependent variable:<br>Log(Anti-Muslim hate crimes) | (1)<br>No hate groups | (2)<br>Any hate group | (3)<br>Few hate crimes | (4)<br>Many hate crimes |
|---|---|---|---|---|
| Log(Twitter Usage) x Year=2010 | -0.01* | 0.01 | -0.00 | -0.00 |
| | (0.01) | (0.03) | (0.00) | (0.01) |
| Log(Twitter Usage) x Year=2011 | -0.00 | 0.00 | -0.00 | 0.00 |
| | (0.01) | (0.03) | (0.00) | (0.01) |
| Log(Twitter Usage) x Year=2012 | 0.00 | -0.01 | -0.00 | -0.00 |
| | (0.01) | (0.04) | (0.00) | (0.02) |
| Log(Twitter Usage) x Year=2013 | -0.00 | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.03) | (0.00) | (0.01) |
| Log(Twitter Usage) x Year=2015 | 0.01 | 0.09*** | 0.00 | 0.06*** |
| | (0.01) | (0.03) | (0.00) | (0.01) |
| Log(Twitter Usage) x Year=2016 | 0.01 | 0.14*** | 0.00 | 0.08*** |
| | (0.01) | (0.03) | (0.00) | (0.02) |
| Log(Twitter Usage) x Year=2017 | -0.00 | 0.06* | -0.00 | 0.03 |
| | (0.01) | (0.03) | (0.00) | (0.02) |
| County FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Pop. deciles x Year FE | Yes | Yes | Yes | Yes |
| Observations | 22,024 | 2,832 | 12,432 | 12,432 |

*Notes:* This table presents panel event study regressions where the dependent variable is the log number of hate crimes against Muslims (with one added inside). We standardized the variables to have a mean of zero and standard deviation of one. The sample period is 2010 to 2017. 2014 is the excluded period. $Log(SXSW followers)$ is the number of local SXSW followers that joined Twitter in March 2007. The existence of hate groups is based on data from the Southern Poverty Law Center (SPLC). The number of hate crimes in the pre-period is based on the total number of hate crimes per capita the FBI registered in a county between 1991 and 2014, split at the 50th percentile. All regressions control for the interaction of population deciles with year dummies. Standard errors in parentheses are clustered by state. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.21—: 2SLS - Social Media and the Rise in Hate Crimes Against Muslims (Tweet Based Measure)**

| | ΔLog(Hate crimes against Muslims) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Panel A: Reduced form** | | | | | | | |
| SXSW Tweet (March 2007) | 0.086*** | 0.095*** | 0.090*** | 0.088*** | 0.088*** | 0.088*** | 0.088*** |
| | (0.027) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) | (0.028) |
| **Panel B: 2SLS** | | | | | | | |
| Log(Twitter users) | 0.201*** | 0.247*** | 0.240*** | 0.279*** | 0.286*** | 0.299*** | 0.300*** |
| | (0.064) | (0.070) | (0.074) | (0.089) | (0.093) | (0.104) | (0.102) |
| Weak IV 95% AR confidence set | [0.095; 0.346] | [0.131; 0.404] | [0.103; 0.407] | [0.131; 0.496] | [0.132; 0.512] | [0.128; 0.571] | [0.132; 0.567] |
| SXSW Tweet (pre) | -0.040 | -0.036 | -0.041 | -0.055 | -0.055 | -0.054 | -0.049 |
| | (0.059) | (0.060) | (0.055) | (0.055) | (0.055) | (0.056) | (0.054) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Population controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Geographical controls | | Yes | Yes | Yes | Yes | Yes | Yes |
| Race and religion controls | | | Yes | Yes | Yes | Yes | Yes |
| Socioeconomic controls | | | | Yes | Yes | Yes | Yes |
| Media controls | | | | | Yes | Yes | Yes |
| Election control | | | | | | Yes | Yes |
| Crime controls | | | | | | | Yes |
| Observations | 3,107 | 3,107 | 3,107 | 3,106 | 3,105 | 3,105 | 3,105 |
| Mean of DV | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 |
| Robust F-stat. | 25.99 | 23.46 | 29.78 | 22.66 | 21.03 | 16.79 | 19.52 |

*Notes:* This table presents county-level OLS and IV regressions where the dependent variable is the log change in hate crimes against Muslims between 2010 and 2017. *Log(Twitter usage)* is instrumented using the number of users who started following SXSW in March 2007. *SXSW followers, Pre* is the number of SXSW followers who registered at some point in 2006. All regressions control for population deciles and state fixed effects (not shown). Demographic controls include population growth between 2000 and 2016 as well as age cohort controls for the share of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, and those over 50. Race and religion controls contains the share of people identifying as white, African American, Native American or Pacific Islander, Asian, Hispanic, or Muslim. Socioeconomic controls include the poverty rate, unemployment rate, local GINI index, the share of uninsured individuals, log median household income, the share of high school graduates, the share of people with a graduate degree, as well as the employment shares in agriculture, information technology, manufacturing, nontradables, construction and real estate, utilities, business services, or other sectors. Media controls include the viewership share of Fox News, the cable TV spending to population ratio, and the prime time TV viewership to population ratio. Election control is the county-level vote share of the Republican party in 2012. Crime controls are the rates of violent or property crime from the FBI. Geographical controls include the linear distance from the SXSW festival location (Austin, Texas), population density, and the natural logarithm of county size. Weak IV 95% Anderson-Rubin (AR) confidence sets are calculated using the two-step approach of Andrews (2018) using the Stata package from Sun (2018). For the just-identified case we study here, the "robust" $F$-stat. is equivalent to the "Kleibergen-Paap" or the "effective" $F$-statistic of Olea and Pflueger (2013). Robust standard errors in parentheses are clustered by state. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.22—: Robustness - Alternative Measures of Twitter Usage**

| | Survey # households using Twitter (1) | Survey % households using Twitter (2) | GESIS Tweets (Pre-Trump) (3) | GESIS Twitter users (4) |
|---|---|---|---|---|
| **Panel A: First stage - Twitter usage** | | | | |
| Log(SXSW followers, March 2007) | 0.440*** | 0.080*** | 0.443*** | 0.461*** |
| | (0.041) | (0.018) | (0.061) | (0.061) |
| **Panel B: OLS - Hate crimes against Muslims** | | | | |
| Twitter measure | 0.061*** | 0.020* | 0.018*** | 0.019*** |
| | (0.019) | (0.010) | (0.006) | (0.006) |
| **Panel C: 2SLS - Hate crimes against Muslims** | | | | |
| Twitter measure | 0.156** | 0.857** | 0.155** | 0.149** |
| | (0.066) | (0.383) | (0.071) | (0.068) |
| Weak IV 95% AR confidence set | [0.033; 0.279] | [0.147; 10.792] | [0.037; 0.301] | [0.036; 0.288] |
| Log(SXSW followers, Pre) | 0.022 | -0.010 | 0.016 | 0.016 |
| | (0.064) | (0.088) | (0.072) | (0.071) |
| Observations | 3,106 | 3,106 | 3,107 | 3,107 |
| Mean of DV | 0.019 | 0.019 | 0.019 | 0.019 |
| SD of Twitter measure | 1.474 | 0.549 | 1.925 | 1.908 |
| Robust F-stat. | 114.10 | 20.59 | 53.15 | 58.04 |

*Notes:* This table presents county-level OLS, reduced form, and IV regressions where the dependent variable is the log change in hate crimes against Muslims between 2010 and 2017. *Twitter usage measure* is the measure listed in the top row, instrumented using the number of users who started following SXSW in March 2007 (in log with 1 added inside). *SXSW followers, Pre* is the number of SXSW followers who registered at some point in 2006 (in log with 1 added inside). All regressions control for population deciles and state fixed effects, as well as demographic controls including population growth between 2000 and 2016 as well as age cohort controls for the share of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, and those over 50. Weak IV 95% Anderson-Rubin (AR) confidence sets are calculated using the two-step approach of Andrews (2018) using the Stata package from Sun (2018). For the just-identified case we study here, the "robust" $F$-stat. is equivalent to the "Kleibergen-Paap" or the "effective" $F$-statistic of Olea and Pflueger (2013). Robust standard errors in parentheses are clustered by state. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.23—: Further Robustness - Social Media and the Rise in Hate Crimes Against Muslims

| | Pop. weights (1) | Change since 1990 (2) | Log hate crimes (3) | Drop zero change counties (4) | Drop potentially nonreporting counties (5) | Drop counties with few Muslims (6) | Only neighbouring counties (7) | Drop zero follower counties (8) |
|---|---|---|---|---|---|---|---|---|
| **Panel A: OLS** | | | | | | | | |
| Log(Twitter users) | 0.091*** | 0.056*** | 0.145*** | 0.056** | 0.042*** | 0.069*** | 0.051*** | 0.077*** |
| | (0.022) | (0.012) | (0.034) | (0.025) | (0.010) | (0.019) | (0.014) | (0.027) |
| **Panel B: Reduced form** | | | | | | | | |
| Log(SXSW followers, March 2007) | 0.102*** | 0.138*** | 0.302*** | 0.100** | 0.071** | 0.074** | 0.069** | 0.105** |
| | (0.038) | (0.035) | (0.066) | (0.049) | (0.032) | (0.034) | (0.033) | (0.040) |
| **Panel C: 2SLS** | | | | | | | | |
| Log(Twitter users) | 0.160** | 0.197*** | 0.518*** | 0.182* | 0.121** | 0.133** | 0.123** | 0.192** |
| | (0.062) | (0.051) | (0.108) | (0.091) | (0.054) | (0.062) | (0.061) | (0.087) |
| Weak IV 95% AR confidence set | [0.057; 0.287] | [0.132; 0.342] | [0.317; 0.719] | [0.017; 0.364] | [0.020; 0.222] | [0.020; 0.259] | [0.011; 0.247] | [0.054; 0.379] |
| Log(SXSW followers, Pre) | -0.015 | -0.004 | 0.060 | 0.006 | 0.020 | 0.030 | 0.016 | 0.003 |
| | (0.067) | (0.069) | (0.162) | (0.094) | (0.070) | (0.076) | (0.075) | (0.080) |
| Observations | 3,107 | 3,107 | 3,107 | 394 | 2,185 | 586 | 1,167 | 172 |
| Mean of DV | 0.164 | 0.024 | 0.088 | 0.150 | 0.027 | 0.085 | 0.041 | 0.150 |
| Robust F-stat. | 63.94 | 86.85 | 86.85 | 53.15 | 92.97 | 89.99 | 74.59 | 47.60 |

*Notes:* This table presents county-level OLS and IV regressions where the dependent variable is the log change in hate crimes against Muslims between 2010 and 2017 in all columns except columns 2 and 3. In column 2, the dependent variable is the log change between 1990 and 2017; in column 3, it is the log number of hate crimes against Muslims in a county after the start of Donald Trump's presidential run on June 16, 2015. *Log(Twitter usage)* is instrumented using the number of users who started following SXSW in March 2007. *SXSW followers, Pre* is the number of SXSW followers who registered at some point in 2006. All regressions control for population deciles, state fixed effects (except in column 1), and demographic controls that include population growth between 2000 and 2016 as well as age cohort controls for the share of people aged 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, and those over 50. Column 4 drops all counties for which the change in hate crimes between 2010 and 2017 was zero. Column 5 drops all counties which never report a hate crime between 1990 and 2017. Column 6 drops all counties for which the (rounded) share of Muslims in the county population is zero according to Census data. Column 7 only keeps neighbouring counties that differ in whether they have SXSW followers in March 2007 or not. Column 8 only keeps counties with any SXSW follower in March 2007 or the pre-period. Weak IV 95% Anderson-Rubin (AR) confidence sets are calculated using the two-step approach of Andrews (2018) using the Stata package from Sun (2018). For the just-identified case we study here, the "robust" $F$-stat. is equivalent to the "Kleibergen-Paap" or the "effective" $F$-statistic of Olea and Pflueger (2013). Robust standard errors in parentheses are clustered by state. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.24—: Robustness - Alternative Estimators**

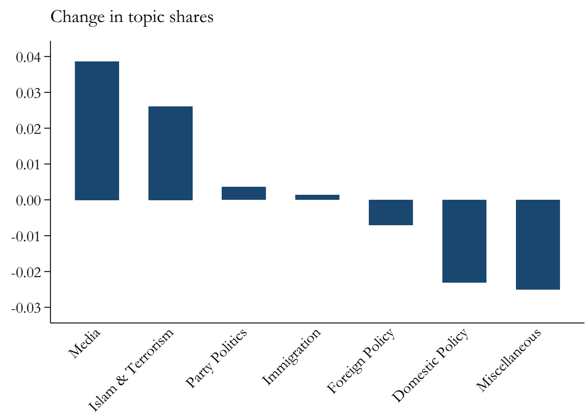
| | IV Probit (1) | IV Poisson (2) | Inverse Hyperbolic Sine (3) | Index Dependent Variable (4) |
|---|---|---|---|---|
| **Panel A: OLS** | | | | |
| Log(Twitter users) | 0.050*** | 0.242*** | 0.028*** | 0.046*** |
| | (0.008) | (0.027) | (0.008) | (0.017) |
| **Panel B: Reduced form** | | | | |
| Log(SXSW followers, March 2007) | 0.035*** | 0.138*** | 0.064** | 0.183*** |
| | (0.014) | (0.033) | (0.031) | (0.067) |
| **Panel C: 2SLS** | | | | |
| Log(Twitter users) | 0.081*** | 0.287*** | 0.166** | 0.380*** |
| | (0.028) | (0.098) | (0.081) | (0.144) |
| Weak IV 95% AR confidence set | [0.359; 10.191] | | [0.017; 0.315] | [0.115; 0.674] |
| Log(SXSW followers, Pre) | -0.014 | -0.016 | 0.008 | -0.092 |
| | (0.029) | (0.067) | (0.060) | (0.142) |
| Observations | 2,648 | 2,648 | 3,106 | 3,106 |
| Mean of DV | 0.093 | 0.264 | 0.025 | 0.031 |

*Notes:* This table presents county-level OLS, reduced form, and IV regressions where the dependent variable is measure of hate crimes against Muslims. Column 1 reports the results from an IV probit regression estimated using maximum likelihood, where the dependent variable is a dummy for counties with an increase in hate crimes against Muslims (and 0 otherwise). Column 2 estimates a Poisson regression, where the dependent variable is the total number of hate crimes after Trump's presidential campaign start. Column 3 replaces the dependent variable with the change in the inverse hyperbolic sine of hate crimes, and the Twitter variables with their inverse hyperbolic sine (instead of log(1+)). Column 4 recodes the dependent variable into an index equal to 1 for increases, -1 for decreases, and 0 for no changes in hate crimes. All regressions control for population deciles and state fixed effects, as well as demographic controls, geographical controls, and race and religion controls, and socioeconomic controls. Weak IV 95% Anderson-Rubin (AR) confidence sets are calculated using the two-step approach of Andrews (2018) using the Stata package from Sun (2018). For the just-identified case we study here, the "robust" $F$-stat. is equivalent to the "Kleibergen-Paap" or the "effective" $F$-statistic of Olea and Pflueger (2013). Robust standard errors in parentheses are clustered by state. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

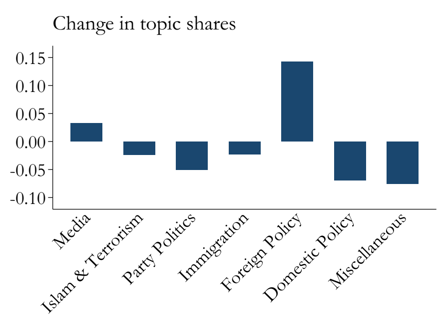
## Appendix 3: Additional Time Series Evidence

**Figure A.6. : Shift in Topics of Trump's Tweets During Events**

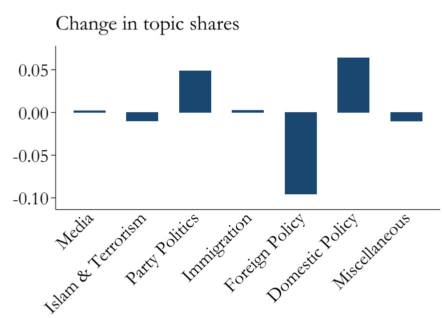
**(a) Golf Days**




**(b) Travel Abroad**



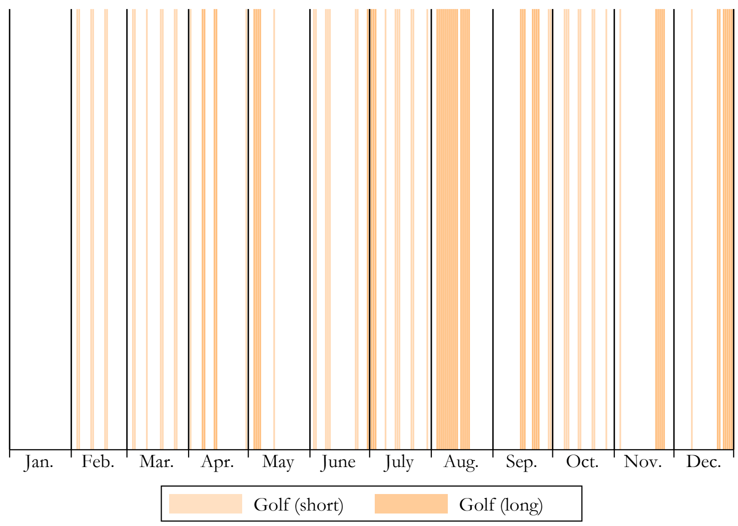

**(c) Policy Briefing**



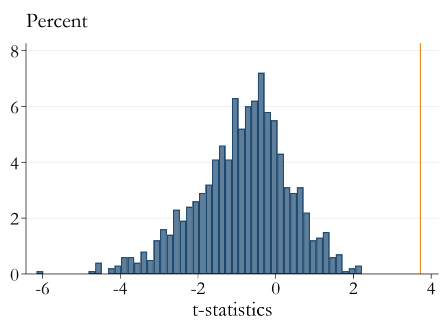

*Notes:* This figure shows how the content of Donald Trump's tweets changes on days when he plays golfs (Panel a), he is traveling abroad (Panel b) or receives a policy briefing (Panel c), based on the official presidential schedule. Topics are based on the independent hand-coding of three research assistants.

**Figure A.7. : Trump's Golf Days**

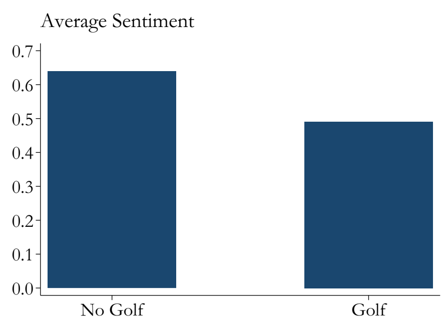
**(a) Trump's Golf Days in 2017**




**(b) Randomization Test for Golf Days**




**(c) Golf Days and Sentiment**




*Notes:* Panel (a) plots the days in 2017 when Donald Trump played golf. *Golf (long)* indicates three or more consecutive days of golfing. Panel (b) visualizes the distribution of $t$-statistics from a randomization test of the first stage regression of Trump's tweets about Muslims on placebo golf days. In particular, we create 1,000 placebo sets of 92 golf days, which is the number of times Trump golfed in 2017. We then regress the log number of Trump's tweets about Muslims on these dummies using the baseline specification in Equation (4) and report the resulting $t$-statistics. The orange line marks our baseline point estimate. Panel (c) plots the average sentiment of Donald Trump's tweets on golf and non-golf days. Lower values mean more negative sentiment. The sentiment was independently hand-coded using a scale from -2 (very negative) to 2 (very positive).

**Table A.25—: Time Series - Split By Pre-Existing Sentiment**

| | No terror attacks | Fox News Muslim Coverage Low | High |
|---|---|---|---|
| | (1) | (2) | (3) |
| **Panel A: First stage - Log(Trump tweets about Muslims)** | | | |
| Trump golfs | 0.078*** | 0.085** | 0.121*** |
| | (0.025) | (0.042) | (0.047) |
| **Panel B: OLS - Log(Hate crimes against Muslims) in t+2** | | | |
| Log(1+Muslim Trump tweets) | 0.194** | 0.120 | 0.074 |
| | (0.095) | (0.102) | (0.127) |
| **Panel C: Reduced form - Log(Hate crimes against Muslims) in t+2** | | | |
| Trump golfs | 0.162** | 0.154* | 0.165 |
| | (0.077) | (0.082) | (0.118) |
| **Panel D: 2SLS - Log(Hate crimes against Muslims) in t+2** | | | |
| Log(1+Muslim Trump tweets) | 2.094* | 1.815* | 1.370 |
| | (1.183) | (1.115) | (1.268) |
| Fixed effects (month, day of week) | Yes | Yes | Yes |
| Time trend | Yes | Yes | Yes |
| Observations | 322 | 192 | 171 |
| Robust F-stat. | 8.78 | 3.59 | 5.84 |

*Notes:* This table presents OLS and IV regressions where the dependent variable is the number of hate crimes against Muslims on any given day based on FBI data. We use a dummy for days on which President Donald Trump golfs used as an instrument for his tweets about Muslims. Column 1 drops days with terror attacks from the sample. Columns 2 and 3 divide the sample based on whether the coverage of Muslim-related topics on Fox News on the day before the Trump tweet/golfing is above or below its median value. The sample year is 2017. All regressions include day-of-week and year-month dummies, linear and quadratic time trends as well as a dummy for whether Trump's golfing is the first of a series of golf days. See online appendix for more details on data and variable construction. Newey-West standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.26—: Time Series Regression Full Period**

| | Baseline (1) | Add lagged dependent variable (2) | Add total tweets control (3) | Use Trump Tweet dummy (4) |
|---|---|---|---|---|
| **Panel A: Before campaign announcement** | | | | |
| Log(Muslim Trump tweets) | 0.009 | 0.009 | 0.007 | 0.028 |
| | (0.007) | (0.007) | (0.007) | (0.035) |
| Fixed effects (year, month of year, day of week) | Yes | Yes | Yes | Yes |
| Time trends | Yes | Yes | Yes | Yes |
| Observations | 2,234 | 2,233 | 2,234 | 2,234 |
| $R^2$ (partial) | 0.00 | 0.00 | 0.00 | 0.00 |
| **Panel B: After campaign announcement** | | | | |
| Log(Muslim Trump tweets) | 0.039** | 0.037** | 0.035** | 0.121** |
| | (0.016) | (0.016) | (0.016) | (0.057) |
| Fixed effects (year, month of year, day of week) | Yes | Yes | Yes | Yes |
| Time trends | Yes | Yes | Yes | Yes |
| Observations | 1,295 | 1,294 | 1,295 | 1,295 |
| $R^2$ (partial) | 0.01 | 0.01 | 0.01 | 0.01 |

*Notes:* This table presents OLS regressions where the dependent variable is the number of hate crimes against the group in the top row on any given day based on FBI data. The sample is split into the period before and after June 16, 2015 when Trump announced his presidential campaign. All regressions include day-of-week and year-month dummies as well as linear and quadratic time trends. Partial $R^2$ excludes these controls. See online appendix for more details on data and variable construction. Newey-West standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.27—: Robustness Time Series 2SLS Regressions

| | Baseline (1) | Add 7 lagged dependent variables (2) | Add golf holiday control (3) | Add previous week golf control (4) | Use Trump Tweet dummy (5) | Use only NYT golf count (6) | Use alternative golf count (7) | Trump in WH control (8) |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Log(Hate crimes against Muslims) in $t+2$** | | | | | | | | |
| Log(1+Muslim Trump tweets) | 1.609** | 1.677* | 1.607** | 1.616** | 1.391* | 1.736** | 1.566* | 1.336* |
| | (0.791) | (0.948) | (0.820) | (0.791) | (0.727) | (0.831) | (0.821) | (0.683) |
| **Panel B: Log(News reports about Muslims) in $t$** | | | | | | | | |
| Log(1+Muslim Trump tweets) | 2.701** | 2.689** | 2.614** | 2.673** | 2.335** | 2.672** | 2.869** | 2.688** |
| | (1.114) | (1.208) | (1.075) | (1.110) | (1.082) | (1.184) | (1.150) | (1.078) |
| **Panel C: Log(New content about Muslims by Trump Twitter followers) in $t$** | | | | | | | | |
| Log(1+Muslim Trump tweets) | 1.151** | 1.008* | 1.233*** | 1.155** | 0.996** | 1.032* | 1.206** | 0.750 |
| | (0.469) | (0.561) | (0.451) | (0.467) | (0.436) | (0.541) | (0.503) | (0.678) |
| Fixed effects (month, day of week) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 364 | 359 | 364 | 364 | 364 | 364 | 364 | 342 |
| Robust F-stat. | 13.02 | 12.08 | 12.80 | 13.40 | 11.81 | 10.45 | 12.56 | 10.47 |

*Notes:* This table presents IV regressions where the dependent variable is listed in the panel header. We use a dummy for days on which President Donald Trump golfs used as an instrument for his tweets about Muslims. Column 2 controls for seven lags of the dependent variable. Column 3 controls for the temperature on the golf day in Washington, D.C.. Column 4 controls for whether Trump golfed in the previous week. Column 5 replaces the number of Muslim Trump tweets with a dummy for whether Trump sends any tweet about Muslims. Column 6 replaces the main measure $Trump\ golfs$ with one that only uses information from the New York Times (ignoring that contained in his presidential schedule). Column 7 uses an alternative golf count that incorporates information from $trumpgolfcount.com$. Column 8 controls for whether Trump is in the White House, travelling, or in a presidential meeting. The sample year is 2017, for which we have information on Trump's golfing. All regressions include day-of-week and year-month dummies, linear and quadratic time trends as well as a dummy for whether Trump's golfing is the first of a series of golf days. See online appendix for more details on data and variable construction. Newey-West standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.28—: Time Series - Split by Type of Hate Crime

| | Any (1) | Vandalism (2) | Theft (3) | Burglary (4) | Robbery (5) | Assault (6) |
|---|---|---|---|---|---|---|
| **Panel A: OLS** | | | | | | |
| Log(1+Muslim Trump tweets) | 0.109 | 0.027 | 0.023 | 0.093** | 0.011 | 0.009 |
| | (0.071) | (0.053) | (0.033) | (0.042) | (0.014) | (0.063) |
| **Panel B: Reduced form** | | | | | | |
| Trump golfs | 0.164** | 0.136** | -0.003 | 0.022 | -0.007 | 0.071 |
| | (0.069) | (0.055) | (0.014) | (0.015) | (0.013) | (0.069) |
| **Panel C: 2SLS** | | | | | | |
| Log(1+Muslim Trump tweets) | 1.609** | 1.338** | -0.033 | 0.216 | -0.065 | 0.693 |
| | (0.791) | (0.621) | (0.132) | (0.148) | (0.131) | (0.712) |
| Weak IV 95% AR confidence set | [0.278; 40.036] | [0.293; 30.245] | [-0.308; 0.268] | [-0.091; 0.581] | [-0.441; 0.156] | [-0.646; 20.595] |
| Fixed effects (month, day of week) | Yes | Yes | Yes | Yes | Yes | Yes |
| Time trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 363 | 363 | 363 | 363 | 363 | 363 |
| Robust F-stat. | 13.15 | 13.15 | 13.15 | 13.15 | 13.15 | 13.15 |

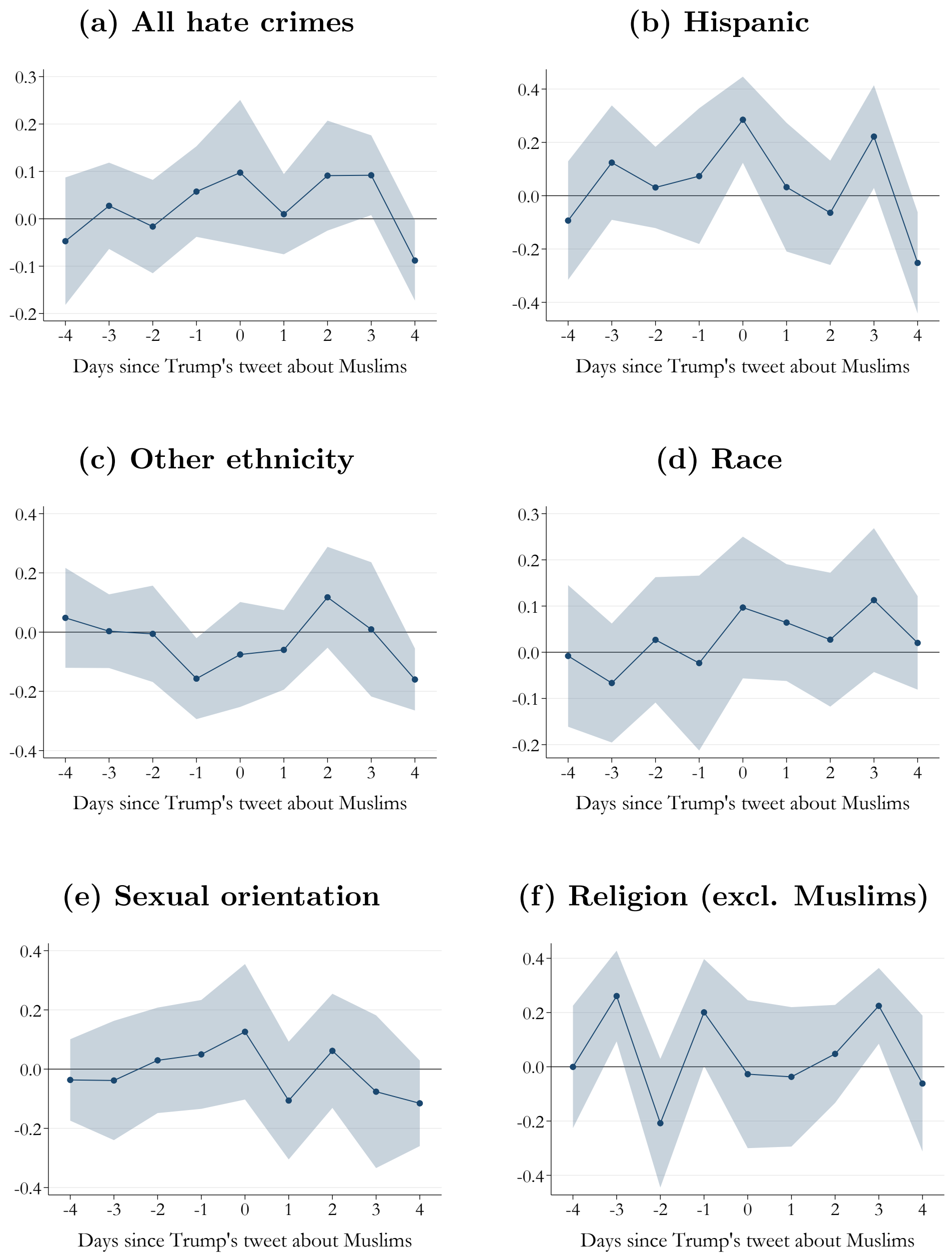
*Notes:* This table presents OLS and IV regressions where the dependent variable is the number of hate crimes against Muslims on any given day based on FBI data. We use a dummy for days on which President Donald Trump golfs used as an instrument for his tweets about Muslims. The sample year is 2017, for which we have information on Trump's golfing. All regressions include day-of-week and year-month dummies, linear and quadratic time trends as well as a dummy for whether Trump's golfing is the first of a series of golf days. See online appendix for more details on data and variable construction. Newey-West standard errors are reported in parentheses. Weak IV 95% Anderson-Rubin (AR) confidence sets are calculated using the two-step approach of Andrews (2018) with the Stata package from Sun (2018). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.29—: Time Series - Split by Motivating Bias**

| | All (1) | Hispanic (2) | Other Ethnicity (3) | Race (4) | Sexual Orientation (5) | Religion (excl. Muslims) (6) |
|---|---|---|---|---|---|---|
| **Panel A: OLS** | | | | | | |
| Log(1+Muslim Trump tweets) | 0.108** | 0.033 | 0.236** | 0.015 | 0.051 | 0.136* |
| | (0.049) | (0.076) | (0.100) | (0.072) | (0.071) | (0.073) |
| **Panel B: Reduced form** | | | | | | |
| Trump golfs | 0.035 | -0.149** | 0.046 | 0.054 | 0.007 | 0.056 |
| | (0.049) | (0.064) | (0.078) | (0.060) | (0.067) | (0.063) |
| **Panel C: 2SLS** | | | | | | |
| Log(1+Muslim Trump tweets) | 0.343 | -1.465* | 0.450 | 0.529 | 0.065 | 0.547 |
| | (0.465) | (0.769) | (0.749) | (0.586) | (0.666) | (0.580) |
| Weak IV 95% AR confidence set | [-0.717; 10.310] | [-30.975; -0.323] | [-10.255; 20.007] | [-0.689; 10.864] | [-10.188; 10.714] | [-0.887; 10.752] |
| Fixed effects (month, day of week) | Yes | Yes | Yes | Yes | Yes | Yes |
| Time trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 363 | 363 | 363 | 363 | 363 | 363 |
| Robust F-stat. | 13.15 | 13.15 | 13.15 | 13.15 | 13.15 | 13.15 |

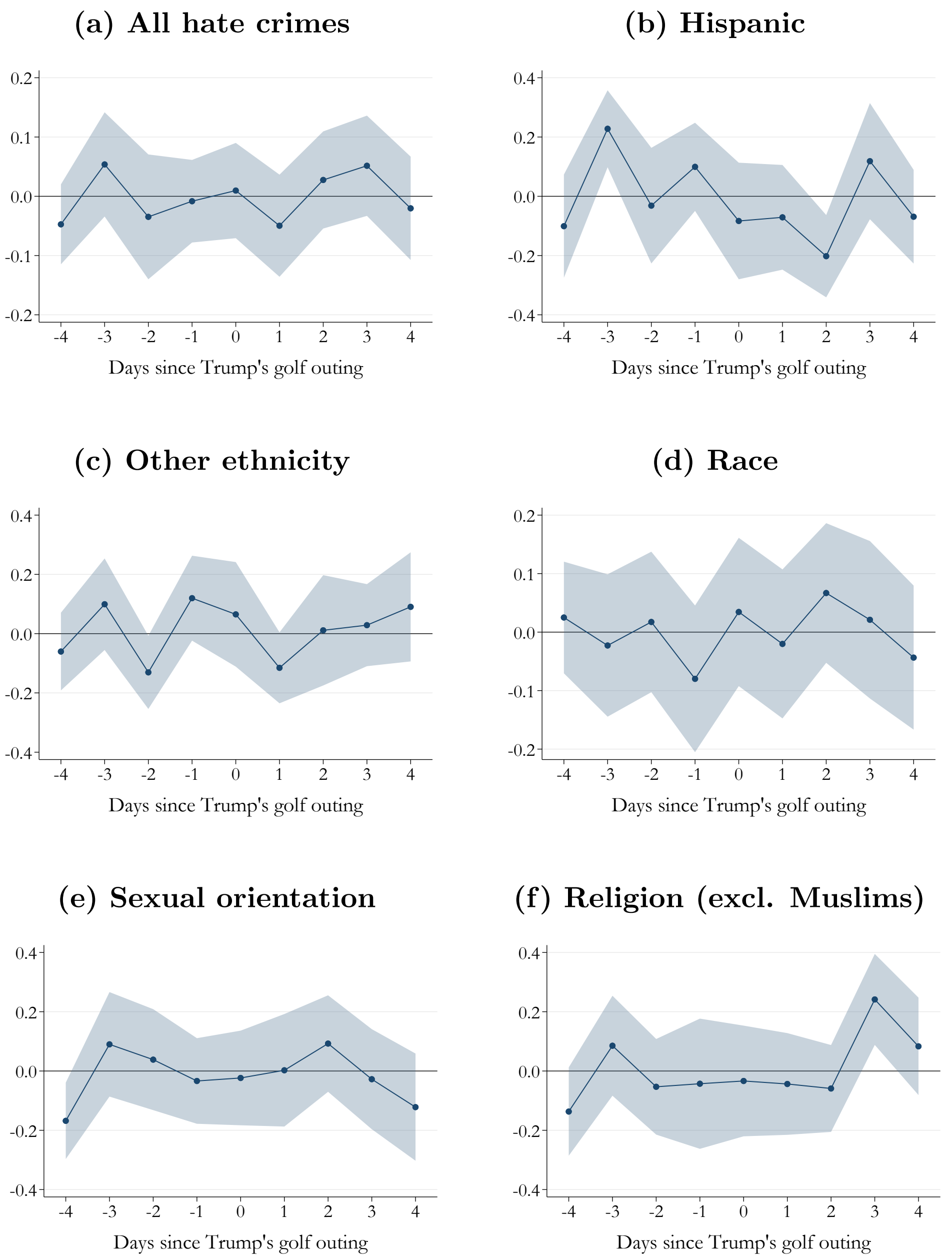
*Notes:* This table presents OLS and IV regressions where the dependent variable is the number of hate crimes against the group in the top row on any given day based on FBI data. We use a dummy for days on which Trump golfs used as an instrument for his tweets about Muslims. The sample year is 2017, for which we have information on Trump's golfing. All regressions include day-of-week and year-month dummies, linear and quadratic time trends, as well as a dummy for whether Trump's golfing is the first of a series of golf days. See online appendix for more details on data and variable construction. Newey-West standard errors are reported in parentheses. Weak IV 95% Anderson-Rubin (AR) confidence sets are calculated using the two-step approach of Andrews (2018) with the Stata package from Sun (2018). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Figure A.8. : OLS Event Study Graphs – Split by Motivating Bias**



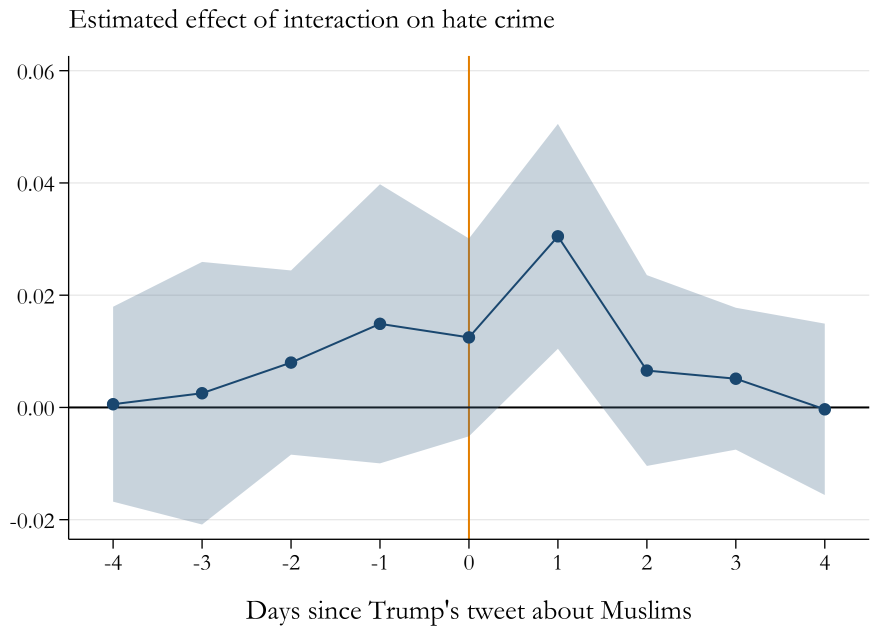

*Notes:* These figures plot the $\beta_\tau$ coefficients from dynamic versions of equations 4 and 5 of the type $Y_t = \alpha + \sum_{\tau=-4}^{4} \beta_\tau \cdot Trump\ tweets_t + \mathbf{X}'_{\mathbf{t}-\tau} + \epsilon_t$. $Y_t$ refers to the number of hate crimes in the top row (in natural logarithm + 1). All regressions include linear and quadratic time trends; a full set of day of week and year-month dummies; and four lags of dummies for the incidence of terror attacks in the US and Europe. The sample period is the year 2017. The shaded areas are 95% confidence intervals based on Newey-West standard errors.

**Figure A.9. : Reduced Form Event Study Graphs – Split by Motivating Bias**




*Notes:* These figures plot the $\beta_\tau$ coefficients from dynamic versions of equations 4 and 5 of the type $Y_t = \alpha + \sum_{\tau=-4}^{4} \beta_\tau \cdot Trump\ golfs_t + \mathbf{X'_{t-\tau}} + \epsilon_t$. $Y_t$ refers to the number of hate crimes in the top row (in natural logarithm + 1). All regressions include linear and quadratic time trends; a full set of day of week and year-month dummies; and four lags of dummies for the incidence of terror attacks in the US and Europe. The sample period is the year 2017. The shaded areas are 95% confidence intervals based on Newey-West standard errors.

**Figure A.10. : Panel Event Study - Trump Tweets, Twitter Usage, and Hate Crimes**




*Notes:* This figure plots the coefficients $\beta_t$ from a dynamic version of Equation (6), where we allow values of $t$ between $-4$ and 4 days around Donald Trump's tweets about Muslims. The dependent variable is an indicator for anti-Muslim hate crimes in county $i$ on day $t$. The coefficients are multiplied by 100 for readability. The regression also includes population controls, interacted with day dummies, state $\times$ day fixed effects, and county $\times$ day-of-week fixed effects, and county $\times$ day-of-month fixed effects. The shaded areas are 95% confidence intervals based on standard errors clustered by state.

## Table A.30—: Two-Instrument Panel Regression Reduced Form Results

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Trump golfs × Log(SXSW followers, March 2007) | 0.008 | 0.011 | 0.013 | 0.013 | 0.013 |
| | (0.023) | (0.021) | (0.021) | (0.021) | (0.021) |
| Muslim Trump tweets × Fox News viewership | | | | -0.001 | |
| | | | | (0.002) | |
| Muslim Trump tweets × Republican vote share 2012 | | | | | -0.003 |
| | | | | | (0.003) |
| County FE | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes |
| Pop. deciles × Date FE | Yes | Yes | Yes | Yes | Yes |
| County × Month FE | | Yes | Yes | Yes | Yes |
| State × Day FE | | Yes | Yes | Yes | Yes |
| County × Day of week FE | | | Yes | Yes | Yes |
| County × Day of month FE | | | Yes | Yes | Yes |
| Observations | 1,131,312 | 1,130,948 | 1,130,948 | 1,130,584 | 1,130,948 |
| $R^2$ | 0.02 | 0.07 | 0.17 | 0.17 | 0.17 |

*Notes:* This table presents OLS, reduced form and IV regressions where the dependent variable is an indicator of anti-Muslim hate crimes in county $i$ on day $t$. The coefficients are multiplied by 100 for readability. The independent variable is the interaction of Trump's golf activity with SXSW followers who signed up in March 2007. The variables are standardized to have a mean of zero and standard deviation of one. All regressions include population controls, as well as county and date fixed effects. Some regressions include county × month, state × day, county × day-of-week, or county × day-of-month fixed effects (as indicated). Robust standard errors in parentheses are clustered by state. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.