From Isolation to Radicalization: Anti-Muslim Hostility and Support for ISIS in the West[*]

Tamar Mitts[†]

March 31, 2017

Abstract

What explains online radicalization and support for ISIS in the West? Over the past few years, thousands of individuals have radicalized by consuming extremist content online, many of whom eventually traveled overseas to join the Islamic State. This study examines whether anti-Muslim hostility might drive pro-ISIS radicalization in Europe. Using new geo-referenced data on the online behavior of thousands of Islamic State supporters in France, the United Kingdom, Germany, and Belgium, I study whether the intensity of anti-Muslim hostility at the local (neighborhood/municipality) level is linked to pro-ISIS radicalization on Twitter. Results show that local-level measures of anti-Muslim animosity correlate significantly and substantively with indicators of online radicalization, including posting tweets sympathizing with ISIS, describing life in ISIS-controlled territories, discussing foreign fighters, and expressing anti-West sentiment. High-frequency data surrounding events that stir anti-Muslim hostility – terrorist attacks and anti-Muslim protests in Europe – show the same pattern.

[*]I would like to thank Susanne Baltes, Eli Berman, Abhit Bhandari, Christopher Blattman, Jasper Cooper, Lindsay Dolan, Page Fortna, Grant Gordon, Guy Grossman, Kolby Hanson, Macartan Humphreys, Sarah Khan, Sung Eun Kim, Egor Lazarev, Summer Lindsey, Joshua Mitts, Suresh Naidu, Jacob Shapiro, Kunaal Sharma, Jack Snyder, Camille Strauss-Kahn, and Lauren Young for their advice and feedback on various stages of this project. This research was approved by the Columbia University Institutional Review Board under protocol IRB-AAAQ7657.

[†]Assistant Professor (August 1, 2016), Ford School of Public Policy, University of Michigan. Ph.D. (expected May 2016), Columbia University, Department of Political Science. Email: tm2630@columbia.edu

1 Introduction

Since 2011, about 30,000 foreign fighters traveled to Syria and Iraq to join the efforts of the Islamic State (ISIS), according to a recent assessment by US intelligence analysts (Schmitt and Sengupta, 2015). Fighters travel to ISIS territories from all over the world, and many come from Western countries like France, Britain, Belgium, Germany and the United States. A very large proportion of Western recruits are being radicalized online by consuming extremist content on the Internet and social media (Carter, Maher and Neumann, 2014; Vidino and Hughes, 2015). Radicalization and support for ISIS are not limited to certain social groups or specific national grievances; rather, these individuals come from many different backgrounds, age groups, education, and income levels (Greenberg, 2016). What motivates Westerners to radicalize and support groups like the Islamic State? How can an organization attract so many individuals to a conflict not their own?

This study brings together research on violent extremism and radicalization, along with literature on immigration in the West, to examine how anti-Muslim sentiment is linked to radicalization and support for the Islamic State in European countries. I argue that hostility towards Muslims in the West can lead individuals to seek comfort and acceptance elsewhere, making radical messages promulgated by foreign rebels seem attractive. A large body of research on immigration to the West studies factors that facilitate or inhibit immigrant integration, with a particular focus on economic outcomes (Dancygier and Laitin, 2014). This literature emphasizes the powerful role that natives' attitudes play in this context, and points to cultural, economic, and psychological factors that determine natives' acceptance, or lack of acceptance, of immigrants in social and economic settings (Hainmueller and Hopkins, 2014).

A recent strand of this important body of work has focused on discrimination against Muslim immigrants in particular, empirically documenting the central role of anti-Muslim discrimination in facilitating Muslims' lack of integration. In France, for example, Adida, Laitin and Valfort (2014, 2016) found that Muslims and non-Muslims are often caught in a vicious cycle in which the latter discriminate against the former, falsely equating "Muslim" and "Jihadist," and Muslims, in turn, tend to distrust non-Muslims and withdraw from French society, thus perpetuating their non-assimilation. But this body of research has yet to examine other outcomes of discrimination. Focusing primarily on social and economic integration, it has not systematically considered how native attitudes towards immigrants might increase the likelihood of jihadi radicalization.

One of the most distinctive aspects of the Islamic State's recruitment strategies is its extensive use of social media. The organization not only distributes provocative content to general audiences on the Internet, it uses social networks on *Twitter*, *Facebook*, and related platforms to attract new members from all over the world. Twitter has been widely used by the organization, because it provides technical advantages such as large-scale public dissemination of content (Klausen, 2015). Studies documenting the usage of Twitter by Western foreign fighters have noted that it played a central role in their radicalization process by intensifying their mental and emotional connection to the war events on the ground (Carter, Maher and Neumann, 2014). Potential recruits find it appealing to connect to the organization through Twitter, as the platform enables the anonymous consumption of radical and extremist ideas, without being exposed to the risk of physically interacting with a recruiter (Berger, 2015). In fact, the organization's online radicalization operation is so vast and extensive that many security agencies find it challenging to keep track of every aspect of these activities (Homeland Security Committee, 2015).

In this study, I take advantage of the presence of this widespread radicalization in the West, and the availability of large amounts of public Twitter data, to examine whether anti-Muslim hostility is linked to support for ISIS in Europe. Using an original method described in the body of the article, I collected granular data on the social media activity of about 15,000 accounts of ISIS activists, as well as the full social network of their followers across the world ($N \approx 1.6$ million). I monitored the online behavior of ISIS activists and their followers in real-time, capturing their activity prior to account suspension, and recorded textual and image content, which I use for analysis.

Using computer science methods to predict the physical geographic location of Twitter users, I matched user-level data to local-level administrative data from the four European countries with the highest share of Western foreign fighters: France, the United Kingdom, Germany, and Belgium (Barrett et al., 2015). I collected data on levels of unemployment, the share of immigrants and asylum seekers in each locality, and local-level vote share for far-right, anti-Muslim parties in recent elections across Europe. As voting for far-right parties strongly correlates with anti-Muslim sentiment,[1] I use vote share for these parties as a local-level measure of anti-Muslim hostility, examining

[1]See more information in the body of the article.

whether it predicts support for ISIS on social media.

I developed several measures of online radicalization and support for ISIS on Twitter. Using supervised machine learning, I classified millions of tweets in English, Arabic, French, and German along various dimensions of ISIS support. These include expressing sympathy with ISIS, tweeting about the life of fighters in ISIS-controlled territories, expressing an interest in traveling to Syria or becoming foreign fighters, and generating anti-West content. In addition, I kept track of which users were flagged as ISIS activists by several hacktivist groups, and also noted when they were suspended from Twitter. I use each of these to measure pro-ISIS radicalization.

Results show that local-level vote share for far-right, anti-Muslim parties in France, the United Kingdom, Germany, and Belgium correlates significantly with online radicalization. In substantive terms, an increase of one percentage point in the local-level vote share for far-right parties is associated with a 6% and 3% increase, respectively, in the probability of a user being flagged as ISIS-affiliated and being among the top 1% posters of radical content. A one percentage-point increase in the right-wing vote share is associated with an average increase of 4,000-9,000 pro-ISIS tweets across the entire sample, including tweets sympathizing with ISIS, expressing anti-West sentiment, and/or interest in foreign fighters and travel to Syria.

As the relationship between online radicalization and support for far-right parties is complex, and may also run in the other direction or be driven by omitted variables, I run several additional tests. First, I take advantage of the high-frequency nature of Twitter data and examine whether events that spur anti-Muslim sentiment, such as terrorist attacks and anti-Muslim protests, are immediately followed by increased posting of pro-ISIS content, especially in areas with high far-right support. Second, I examine whether the results might be driven by the local presence of minority populations. In analyses with data available only in the U.K., I include covariates for the proportion of Muslims, Arabs, Pakistanis, Bangladeshis, and foreign-born in each local area. After controlling for these covariates—many of which are negatively or not correlated with radicalization measures—I find that vote share for the far-right remains strongly positively correlated with posting pro-ISIS content on Twitter. Taken together, the findings are consistent with the argument that online radicalization and support for ISIS in the West are driven by exposure to anti-Muslim animosity.

2 Radicalization

Why do individuals living in Western countries begin to support groups like the Islamic State? What attracts people to ISIS's extremist ideology? A large literature has sought to explain the causes of radicalization and violent extremism, especially in the context of militant Jihad. Most agree that radicalization involves a change in ideology or beliefs that support indiscriminate violence against civilians for political reasons, or a group that represents this ideology and actions (Borum, 2011; Crossett and Spitaletta, 2010; McCauley and Moskalenko, 2008; Wilner and Dubouloz, 2010; Sedgwick, 2010).[2] Theories on the drivers of radicalization vary in their focus, some pointing to structural factors such as social or political grievances (Bass, 2014; Lyons-Padilla et al., 2015), others emphasizing opportunity-based explanations such as the role of social networks and economic incentives (Dalgaard-Nielsen, 2010; Wiktorowicz, 2005; Mousseau, 2011), and others looking at individual-level psychological explanations such as thrill and identity seeking and the role of triggering events (Nussio, 2017; Bayman and Shapiro, 2014; Bass, 2014).

This paper focuses on a slightly different explanation, arguing that experiences of social isolation can prompt a process of radicalization. Specifically, I contend that local, personal exposure to anti-Muslim hostility can trigger individuals to open up to extremist jihadi ideologies. Prior research on jihadi radicalization in Western countries has shown, using case studies, that experiences of discrimination led individuals to radicalize (Wiktorowicz, 2005; Wilner and Dubouloz, 2010; Borum, 2011). While not focusing on radicalization as an outcome, related work on the impact of anti-Muslim discrimination has shown that it tends to inhibit integration and assimilation (Adida, Laitin and Valfort, 2016; Gould and Klor, 2014; Bryan, 2005; Abdo, 2006). Indeed, recent evidence from the United States suggests that failed integration of Muslim immigrants can increase support for violent extremism (Lyons-Padilla et al., 2015).

I argue that groups like the Islamic State seek to attract isolated individuals in the West, by providing an alternative 'virtual community' on the Internet and social media. A large number of people who radicalized and joined ISIS from Western countries began embracing the organization's

[2] In this study, I use the term 'radicalization' more narrowly, i.e., to refer simply to expressions of support for and sympathy with the Islamic State—a group that represents an extreme ideology and carries out indiscriminate violence against civilians for political reasons.

ideology when searching for belonging and identity (Vidino and Hughes, 2015; Shane, Apuzzo and Schmitt, 2015). Hoda Muthana, for example, an American student from Alabama, was radicalized on social media after opening a secret Twitter account without her parents' knowledge. After interacting with ISIS supporters on Twitter, she adopted radical interpretations of Islam and eventually traveled to Syria to join the organization (Hall, 2015). Ali Shukri Amin, an American teenager from Virginia, found solace from his troubled life in the virtual communities of ISIS activists on Twitter. In the end, Amin disconnected from his family and friends, spread ISIS propaganda to thousands of followers online, and recruited one of his friends to travel to Syria to become a foreign fighter (Shane, Apuzzo and Schmitt, 2015; Robinson, 2015).

Indeed, evidence from the United States collected by the author shows that among over a hundred of individuals charged with providing material support for ISIS or plotting a violent attack on the organization's behalf, about 63% used social media when they were radicalizing, and among those, 86% expressed their support for ISIS in publicly viewable posts.[3] The Internet and social media seem to play a central role in exposing Western individuals to paths of radicalization. These findings are consistent with research on the social media usage of European foreign fighters shows that online social networks played a dominant role in fighters' radicalization process (Carter, Maher and Neumann, 2014). However, our knowledge of the online behavior of ISIS supporters and its relation to real-world events is currently very limited. In this paper, I examine whether online indicators of pro-ISIS radicalization are stronger for individuals experiencing greater levels of anti-Muslim hostility.

2.1 Anti-Muslim hostility and support for far-right parties

Animosity against Muslims in the West has been rising in recent years, especially after 9/11 (Stack, 2015; Burrows, 2016). Examples include setting fire to mosques, spreading anti-Muslim graffiti, and physically attacking individuals who practice Islam. Take the case of Ms. Khola Hasan, an Islamic scholar from the U.K.'s Epping Forest region, who has been targeted by anti-Muslim violence multiple times in recent years. In an interview with *The Guardian*, she said, "I was walking down Epping High Street and a man shouted at me 'You bloody ISIS supporter.' Another time ... someone

[3]See full details in the Supplementary Information materials.

stopped their car and threw an empty glass bottle at me. I was absolutely terrified." (Flaig, 2016)

Epping Forest is among the constituencies with the highest vote share for far-right parties in the United Kingdom. In the 2015 general elections, over 18% of its voters voted for far-right parties, putting the locality at the top 10% of far-right vote share in the country. A similar pattern is observed in other European localities with high far-right support. In Dartford, U.K., right-wing activists recently launched an "anti-halal operation," targeting Muslim restaurants selling halal food with the claim that they support terrorism by paying a zakat religious tax (Kent Online, 2015). In Provins, France, where vote share for the Front National party in the 2015 Departmental Elections was above 37%, a local mosque was recently desecrated with anti-Muslim graffiti (Inge, 2013).

Indeed, far-right parties are one of the most prominent mobilizers of anti-Muslim sentiment in contemporary Europe. A common theme in the platforms of these parties is support for exclusionary, "nativist" populism that combines nationalism and xenophobia, seeking to ostracize groups with certain cultural, religious, or ethnic characteristics (Golder, 2016). For example, France's Front National party has long blamed Muslim immigrants for many of the country's social problems, ranging from unemployment to security and national unity (Adida, Laitin and Valfort, 2016; Front National, 2016).[4]

Several scholars have suggested that far-right voting is strongly linked to anti-Muslim sentiment (Lubbers and Scheepers, 2002; Norris, 2005; Rydgren, 2008). Using data from the European Social Survey Round 7 Data (2014) (ESS Round 7, 2014), I tested the relationship between far-right voting and anti-Muslim attitudes in Europe. Table 1 shows that there is a strong correlation between holding anti-Muslim and anti-immigrant attitudes and self-identifying as a far-right supporter (Panel A) or voting for far-right parties (Panel B).[5] The regressions control for a large number of demographic variables that might also explain anti-Muslim attitudes, such as being native-born,

[4]While the overall popularity of far-right, anti-Muslim parties in Europe has increased nationally, support for these parties still varies significantly at the local level. Figure S16 in the Supplementary Information materials shows the vote share for far-right parties in France, Germany, and the U.K. at the electoral constituency level in national elections taking place in recent years. Research on support for far-right parties in has shown that it tends to be stronger in areas where minority communities form a smaller share of the population (Biggs and Knauss, 2012). In this paper, I use local-level data on vote share for far-right parties as a proxy for local anti-Muslim hostility, and examine whether it is linked to online radicalization and support for ISIS among potential recruits.

[5]The parties used to create the voting measure for the far-right are Front National in France, United Kingdom Independence Party (UKIP) in the United Kingdom, National Democratic Party of Germany (NPD) and Alternative for Germany (AfD) in Germany, and Vlaams Belang in Belgium.

Table 1: Far-right support and anti-Muslim attitudes in Europe

	(1) Do not allow Muslims in country	(2) Disapprove immigration of different race/ethnic groups	(3) Disapprove relative marrying someone from a minority race/ethnic group	(4) Do not want a boss from a minority race/ethnic group	(5) Immigrants make crime worse
			A. Far-right self placement		
Far-right self placement	0.12***	0.37***	0.99***	0.39	0.41**
	(0.03)	(0.07)	(0.27)	(0.24)	(0.18)
Constant	0.05	2.14***	2.09***	1.58***	6.78***
	(0.04)	(0.10)	(0.37)	(0.32)	(0.28)
Demographic controls	✓	✓	✓	✓	✓
R^2	0.054	0.075	0.068	0.075	0.023
Observations	3,850	3,874	3,894	3,867	3,837
			B. Far-right voting		
Voted for far-right party	0.26***	0.65***	1.91***	1.49***	1.23***
	(0.05)	(0.09)	(0.34)	(0.35)	(0.24)
Constant	0.06	2.15***	2.12***	1.56***	6.77***
	(0.04)	(0.09)	(0.37)	(0.32)	(0.28)
Demographic controls	✓	✓	✓	✓	✓
R^2	0.070	0.085	0.076	0.084	0.033
Observations	3,850	3,874	3,894	3,867	3,837

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports the correlations between voting for far-right parties in France, Belgium, Germany, and the United Kingdom and holding anti-Muslim and anti-immigrant attitudes. The *Far-right self placement* variable is an indicator coded 1 for individuals who identify as '10' (farthest on the right) on a 1-10 scale of left-right placement. *Voted for far-right party* is an indicator variable coded 1 for individuals who voted for Front National (FN) in France, United Kingdom Independence Party (UKIP) in the United Kingdom, National Democratic Party of Germany (NPD) and Alternative for Germany (AfD) in Germany, and Vlaams Belang (VB) in Belgium. The table presents estimates from ordinary least squares regressions of the outcome variables reported in columns (1) through (5) on indicators of support for far-right parties, controlling for being native-born, education, income, gender, age, and religion. Data source: European Social Survey Round 7 Data (2014).

education, income, gender, age, and religious beliefs.

These patterns suggest that local-level support for far-right parties can reflect an atmosphere of anti-Muslim hostility. I use sub-national data on vote share for far-right parties to proxy for local anti-Muslim animosity, and examine whether it is linked to online radicalization and support for ISIS among potential recruits located in these areas. In the following section, I explain how I created measures for online support for ISIS by identifying and observing in real-time the content and social media activity of individuals at risk of radicalization.

3 Data

In this section, I describe the original data used in this study. In subsection 3.1, I explain how I identify ISIS activist and follower accounts on Twitter—a nontrivial challenge akin to finding a needle in a haystack. In subsection 3.2, I explain the algorithm that I use to predict the physical geographic locations of Twitter users in my dataset. In subsection 3.3, I define the measures of online radicalization, which serve as the outcome variables in this study, and provide summary statistics on these variables. Finally, in subsection 3.4, I describe the local-level administrative data which are matched to each user on a geographic basis, and thus serve as the independent variables in this study.

3.1 Identifying ISIS activist and follower accounts on Twitter

Finding people on Twitter who are sympathetic to the Islamic State and/or possibly radicalizing is a challenging task. While there are many ISIS accounts active on Twitter—some have estimated as many as 40,000–125,000 (Berger and Morgan, 2015; Isaac, 2016)—this is still a small figure compared to the overall number of Twitter users, which amounts to about 313 million.[6] In a way, it is like finding a needle in a haystack. Previous methods for identifying ISIS supporters on Twitter include measuring the networks of selected seed accounts (Berger and Morgan, 2015; Chatfield, Reddick and Brajawidagda, 2015) and qualitatively analyzing a handful of accounts of recruits known to have migrated to Syria and Iraq (Carter, Maher and Neumann, 2014; Pooley, 2015).

In this project, I identify ISIS accounts by tracking in real-time lists published by several anti-ISIS hacking groups. As the organization's activity on social media intensified in the past several years, groups such as Anonymous and Controlling Section (@CtrlSec) began monitoring social media accounts identified with the organization and publicly flagging them for suspension. At the beginning of 2015, the group @CtrlSec asked social media users to help find ISIS accounts on Twitter (see Figure S11 in the Supplementary Information materials), an effort that led to the suspension of thousands of accounts in a matter of days. Since then, the monitoring, flagging, and suspension

[6] As of August 2016. `http://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/`

of ISIS accounts continues,[7] and this project leverages this information to identify ISIS activists' accounts.

I designed an algorithm that since December 2015 has been continually monitoring and recording Islamic State accounts identified by @CtrlSec (see Figures S13 and S14 in the Supplementary Information materials for examples of such accounts). Immediately upon observing a new account in the @CtrlSec list, I downloaded the complete historical "timeline" of tweets for the account, as well as its user profile, which includes self-described location, time zone, and list of the account's friends and followers.[8] This real-time data collection enabled me to capture information on accounts of about 15,000 ISIS activists before they were deleted from the Internet. In addition, I collected data on the online activity of about 1.6 million followers of these @CtrlSec-identified ISIS accounts, to identify a set of people "at risk" of becoming ISIS activists, as well as about 450,000 friends of these followers. The database, which is described in detail in the Supplementary Information materials, contains user-level information, taken as "snapshots" of each user's profile at various points in time, as well as tweet-level information on over 61 million tweets, collected from all ISIS activist accounts, as well as a subset of the followers. Figure 1 shows the geographic distribution of the accounts of ISIS activists across the world.

3.2 Predicting geographic locations of ISIS activists and followers

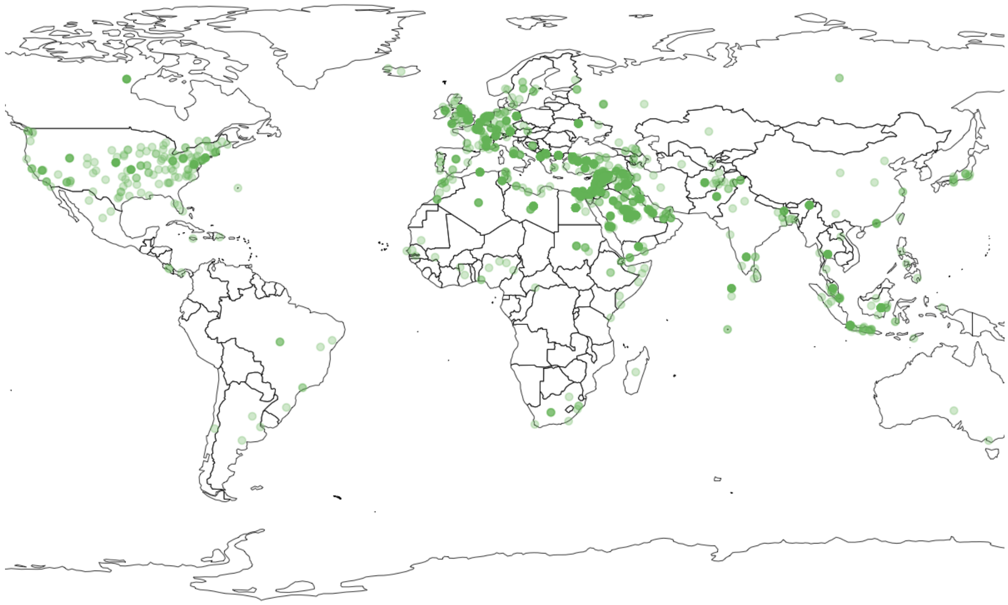
A central aspect of this study involves predicting the geographic location of Islamic State activists and followers on Twitter, in order to match them to geographic data on socio-economic variables that might correlate with online radicalization. Since a very small share of Twitter users enable geo-tagging of their tweets or provide location information in their accounts,[9] social network and computer science researchers have developed methods in recent years to triangulate a user's location based on locations provided by their networks of friends and followers (Backstrom, Sun and Marlow, 2010; McGee, Caverlee and Cheng, 2013; Jurgens et al., 2015). I employ a spatial label propagation

[7] Earlier in 2015, Twitter announced that it has suspended about 125,000 ISIS accounts, many of which are believed to be flagged by @CtrlSec. See: `http://www.nytimes.com/2016/02/06/technology/twitter-account-suspensions-terrorism.html?_r=0`; as well as: `http://www.theatlantic.com/international/archive/2015/10/anonymous-activists-isis-twitter/409312/`

[8] On Twitter, a "friend" of account i is an account that i follows.

[9] For example, in my database, only 26% of the users enable geo-tagging of their tweets, and 37% provide self-described location information.

Figure 1: Predicted locations of ISIS activists on Twitter across the world



Note: The figure plots the predicted locations of accounts flagged as ISIS activists by @CtrlSec. Locations are predicted using a recent method in the computer science literature—spatial label propagation—to predict the geocoordinates of social media users (Jurgens, 2013; Jurgens et al., 2015).

algorithm developed by Jurgens (2013) to predict Twitter users' locations, which performs three rounds of prediction to maximize predictive accuracy.

Spatial label propagation algorithms rely on the finding in social network research that location information in a user's online network is a powerful predictor of a user's offline geographic location (Goldenberg and Levy, 2009; Takhteyev, Gruzd and Wellman, 2012; McGee, Caverlee and Cheng, 2011). While social media platforms allow people to connect with others across the globe, recent studies have found that physical relationships in the offline world still strongly influence online social relationships. When people live their lives offline, they form relationships that subsequently transfer to the online world—e.g., co-workers or classmates who meet offline and then connect on social media platforms. As a result, a large share of individuals' online social network usually includes geographically close friends. Figure S17 in the Supplementary Information materials, which is taken from Jurgens (2013), shows that across various social networks on different platforms, the majority of individuals in the network had at least one friend that was located within 4 kilometers. The Supplementary Information materials provide more information on the details of this location prediction process, as well as a discussion of its out-of-sample predictive accuracy.

While this method is imperfect and subject to prediction error, the rich data that it provides allows us to examine the local-level correlates of online support for Islamic State in Europe. As existing quantitative research on ISIS foreign fighter recruitment has so far remained at the country level, this is an important step forward. In addition, while prediction errors make estimations more noisy, there is little reason to think they are plagued by systematic biases.[10] Location predictions are carried out on a very large and relatively deep network of almost 2 million Twitter users across the world. Location prediction errors are likely to bias the results if they affect the *network* structure of individuals showing support for ISIS, e.g., by leading them to *strategically* choose friends so that their locations are systematically predicted (incorrectly) in areas with higher vote share for far-right parties. Strategic choice of friends in this way is difficult to perform systematically.

Moreover, location prediction is carried out for *all* users in the database and analysis is carried out across thousands of localities in four countries. For systematic biases to be present, location predictions for ISIS supporters would have to appear systematically across countries in a pattern that correlates with far-right party vote-share locally. To address the concern that Internet usage varies across rural and urban areas, regressions control for local population size.

3.3 Measuring online radicalization

I measure online radicalization using various user-level and tweet-level variables from the ISIS activists/followers database. Since my pool of subjects consists of individuals who already follow one or more ISIS accounts, my analysis is limited to people who already show signs of interest in the organization. Nonetheless, since the followers sample consists of a range of accounts—from individuals who are already ISIS activists to accounts that are countering ISIS—being included as a follower in the database does not imply that one is actually radicalizing. To address the concern that I measure anti-ISIS accounts as 'radicalized,' I use textual and social network information to find tweets and users who are more likely to reflect pro-ISIS content.

Online radicalization measures are constructed as follows. First, I employ data from user-level fields to create indicators for whether a given user is flagged as an ISIS activist by @CtrlSec.

[10] A test of the correlation between the prediction errors and far-right vote share shows no systematic relationship. The results of this test are reported in the Supplementary Information materials.

Second, I use data on account suspension to code whether a user is suspended from Twitter for being associated with ISIS. Third, I use the network information in the database to count the number of ISIS accounts that each user follows. Fourth, I create textual measures for the number of pro-ISIS tweets posted by each user along several dimensions of ISIS support.

To generate the textual outcomes, I use supervised machine learning to classify tweets in English, Arabic, French, and German into one or more of these categories:

1. *Sympathy with ISIS* - expressions of support or sympathy with the Islamic State, its ideology and its activities in territories under its control

2. *Life in ISIS territories* - tweets describing the life of ISIS activists in the territories controlled by the Islamic State

3. *Travel to Syria or foreign fighters* - tweets describing interest or intent to travel to Syria, and/or discussion of foreign fighters

4. *Syrian war* - tweets describing events in the Syrian civil war and/or discussion/analysis of those events

5. *Anti-West* - anti-West rhetoric, criticizing Western countries' foreign policy and military operations in the Middle East

6. *Islam* - expressions of faith in the Islamic religion, Islamic quotes, and prayers and/or requests for prayers

While some of these topics may not signal online radicalization—for example, tweets expressing faith in Islam or tweets criticizing the West are likely to be completely benign in most cases—the combination of these with other topics that more directly reflect support for ISIS, can plausibly capture radical content. Therefore, I measure online radicalization by looking at the distribution of tweets across all of these topics combined, coding Twitter users who are on the higher end of the distribution of posting on these topics as more strongly supporting the organization. Table 2 shows examples of English language tweets for each of these topics.

The supervised learning process works as follows. First, human coders from two crowdsourcing platforms, Amazon Mechanical Turk and Crowdflower, labeled a random sample of posts by hand.[11]

[11] See Figure S10 in the Supplementary Information materials for an example of instructions for the classification task in the Crowdflower platform.

Table 2: Examples of tweets in different topics

Sympathy with ISIS
Jihad is the greatest of all deeds #IslamicState
Show everything from the Islamic State and other groups in Syria. It's important to hear all sides of the story.
Assalam o Alaikom to All Islamic State Brothers
In sha Allah we will have honor again #IslamicState
Life in ISIS territories
#Aljazeerah reports from inside the city of #Raqqa and shows how the #IslamicState runs the daily life
English Testimony from a girl in #Yarmouk Camp about the #IslamicState
The glorious and mighty army of the Caliphate: Young kids ready to blow themselves up.
Health services in Islamic state
Wedding of an #ISIS fighter in #Raqqa:
In Ribaat... Nice feeling really; Sit with the bros, drink tea, read Quran, relax & just observe the enemy! #Syria
Travel to Syria or foreign fighters
a lot of foreign fighters still coming in. Seems a lot responding to the call of the scholars of General March, also indicating open way in!
is the door to sham open?
i want your kik please akh, maybe there is sister in my country that have more money and looking for hijra too...
come on join us at syam..
Dutch fighters in ar-Raqqa province #Syria
Syrian war
#IS fighters readying to fight an invasion of Yarmouk Camp by Assad's allies Jaysh Al-Islam and Liwa Sham Al-Rasool
Massive destruction in Douma today after one of Assad's almost daily air strikes on the city. #Syria #Damascus
#Syria - The evil #Assad regime lost Busra al-Harir so they tortured a 6 year old girl out of revenge...
Massive explosion rocked entire of #Ramadi city. No further details yet.. #Iraq #ISIS
Anti-West
America has been at war 222 out of 239 years since 1776. Let that sink for a moment.
If Islamic State terror is evil why would Western State war be good?
US-led wars on terror have killed four million Muslims since 1990
It's sad when I am more afraid of our government then #ISIS ! At least I know #ISIS hates #America #Government =wolves
Why are we shocked at ISIS brutality but not shocked by US British & European brutality?
Islam
Call upon Me; I will respond to you. #Quran 40:60
My identity is in who Allah says I am not in who others say I am. Allah's opinion is the only one that truly matters.
To think that Allah Almighty is present with you at every given moment is the most excellent form of #faith.
The beauty of Sujood is such that you whisper silently in to the ground and it's heard up in the Heavens.
May allah bless you brother.......

Then, an algorithm used information on the words in each labeled post to "learn" the categorization rules and classify unlabled posts.[12] I obtained a random sample of tweets posted by ISIS activists in English, Arabic, French, and German to create a training set for the classification model.[13] Each

[12]See Grimmer and Stewart (2013) for a review and more information on supervised machine learning methods to classify text, and James et al. (2013) for an introduction to machine learning in general. The Supplementary Information materials provide more details on the supervised learning method used in this paper.

[13]English, Arabic, French and German are used in 76% of the tweets in the database. As the proportion of tweets in the database varies by language, the size of the training set accordingly varies for different languages: English ($N = 9,926$), Arabic ($N = 10,631$), French ($N = 6,158$), and German ($N = 3,011$).

tweet was labeled by three coders, and and label(s) were retained for a given tweet only if at least two out of the three coders assigned the same label(s) to the tweet.

Since Twitter textual data are very noisy, and radical pro-ISIS content is rare, many tweets in the database were coded as unrelated to any of the above categories.[14] To facilitate statistical prediction, I follow King and Zeng (2001) and randomly over-sample pro-ISIS tweets and randomly under-sample unrelated tweets to obtain a class proportion of 0.5 for each of the categories, for each topic, for each language. I trained separate logit models using the labeled rebalanced training sets for each category in each language. For all specifications, I used the the elastic-net generalized linear model (Friedman, Hastie and Tibshirani, 2010), selecting the regularization parameter λ by cross-validation to maximize the area under the ROC curve. Using this method, the models were able to predict pro-ISIS content with an in-sample accuracy over 95%. More metrics on the performance of the models for each topic and language are reported in section S3 in the Supplementary Information materials. The classification models for each topic and language were then employed on the full set of tweets in the database to classify each unlabeled tweet as belonging to one or more of these categories. Table S12 in the Supplementary Information materials shows the top 50 words for each topic in English language tweets.

To measure users' posting of radical and pro-ISIS content, I counted the number of tweets classified in these six categories for each user. I also created a combined measure that counted the number of tweets falling into any of these categories. To ensure that I capture users that post highly pro–ISIS content, I created an indicator that is coded 1 for users who are at the top 1% of the distribution of radicalized content posting and 0 otherwise.[15] Panel A in Table 3 provides summary statistics for these various measures of online radicalization.

While these measures only capture expressions of support for the Islamic State in the online world, they are nonetheless a plausible proxy for underlying radicalization. Social media played a central role in the radicalization process of European foreign fighters (Carter, Maher and Neumann, 2014). In the United States, the majority of individuals who attempted to travel overseas to join

[14] See Supplementary Information materials for details on the classes for each outcome and language.

[15] I chose this cutoff in order to be conservative and not erroneously classify as radicalized individuals who post less radical content. As reported in Table S16 in section S7 in the Supplementary Information materials, results hold in estimations with cutoffs using top 5%, 10% 15%, and 20%.

ISIS or planned a violent attack on the organization's behalf used social media when radicalizing. Importantly, most of these individuals have expressed their support for ISIS on social media by posting publicly viewable posts.[16] This suggests that studying radicalization using online measures of ISIS support can be a fruitful way to understand this phenomenon.

Table 3: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
A. Dependent variables					
Tweets with pro-ISIS content (#)	174,479	35.304	90.508	0	1,933
Pro-ISIS content (top 1%)	174,479	0.010	0.099	0	1
Tweets with pro-ISIS content, excluding Islam (#)	174,479	25.712	66.411	0	1,421
Pro-ISIS content, excluding Islam (top 1%)	174,479	0.010	0.099	0	1
Sympathy with ISIS (#)	174,479	4.657	12.297	0	277
Life in ISIS territories (#)	174,479	6.263	16.522	0	308
Travel to Syria or foreign fighters (#)	174,479	6.645	17.195	0	343
Syrian war (#)	174,479	3.707	10.016	0	251
Anti-West (#)	174,479	4.440	11.982	0	287
Islam (#)	174,479	9.592	24.594	0	512
Number of ISIS accounts following	174,474	5.452	23.863	0	3,216
Flagged as an ISIS activist	174,479	0.005	0.070	0	1
Suspended by Twitter	174,474	0.041	0.199	0	1
B. Independent variables					
Far-right vote share (%, local level)	116,493	13.208	9.026	0	53.805
Unemployed (%, local level)	170,654	5.124	2.410	0	41
Immigrants unemployed (%, local level)	90,521	1.889	0.993	0	9
Foreigners/non-citizens (%)	171,077	10.466	7.405	0	89.026
Population	171,548	815,078	1,078,663	3	3,292,365

Note: This table reports summary statistics for the sample of ISIS activist and followers who are predicted to be located in France, Germany, Belgium, and the United Kingdom.

3.4 Independent variables

To create a local-level measure of anti-Muslim hostility, I relied on the finding presented in section 2.1 on the strong link between far-right voting and holding anti-Muslim attitudes. I created local-level measures of support for the far-right by calculating the percent of votes for parties associated

[16] See more details in the Supplementary Information materials.

with far-right positions at the electoral constituency level in France, Germany, Belgium, and the United Kingdom. Table 4 shows the elections and parties used to construct this variable. Using Twitter users' predicted geo-location data (see section 3.2 for more details), I matched users in my database to electoral constituencies, thereby assigning users to different areas with varying degrees of far-right support. Panel B in Table 3 shows that vote share for these parties varies substantially, where some users are located in areas with zero vote share for far-right parties, and others in areas with more than 50% support for these parties.

Table 4: Far-right parties in recent European elections

Country	**Election**	**Far-right parties**
France	2015 departmental elections	Front National (FN)
Germany	2013 Federal elections	National Democratic Party of Germany (NPD); Alternative for Germany (AfD)
United Kingdom	2015 general elections	British Democrats; British National Party; Liberty GB party; National Front party; United Kingdom Independence Party (UKIP)
Belgium	2014 Belgian federal elections	Vlaams Belang (VB)

In addition, I created variables for other socio-economic indicators that might predict online support for ISIS. First, to examine whether local-level unemployment is linked to radicalization, I used official data on unemployment from France, Germany, the United Kingdom and Belgium, at the lowest possible level of aggregation. In France, Germany, and Belgium, the lowest possible level was the town/municipality. In the United Kingdom, data were available at the sub-municipality/neighborhood level.[17] I matched users to their respective areas for which unemployment data exist. As some have hypothesized that unemployment among *immigrants* in particular feeds ISIS radicalization (Grant, 2014), I also created a measure for the share of unemployed immigrants in each location. Panel B in Table 3 provides information on the distribution of these variables across Twitter users in the database.

Second, with the recent debates over the link between refugees and support for ISIS in Europe (Marans, 2015), I looked for variables that might proxy for the presence of refugees in a locality. I use information on the number of asylum seeker centers across localities in France, and the share

[17]In the United Kingdom, statistical local-level data are available at the Mid-level Super Output Areas (MSOA), which are roughly the size of a neighborhood (Office for National Statistics, 2016).

of asylum seeker benefits receivers in localities in Germany.[18] As these two variables are measured on different scales, I created a standardized measure for this combined variable. In addition, I use census data on the share of foreigners or non-citizens in each locality, to examine the extent to which ISIS supporters on Twitter are located in areas with higher shares of non-citizen populations. Table 3 shows the distribution of these variables across users. The Supplementary Information materials provide more details on the data sources and construction of the independent variables.

4 Descriptive analysis

This section presents a few examples that illustrate the kind of content that I collected and its connection to real-world events. On June 29, 2014, after conquering territories in Syria and Iraq, ISIS declared the establishment of a caliphate in an online statement distributed through Twitter and the group's media center,[19] calling all Muslims to pledge allegiance to it:

> *"So rush O Muslims and gather around your khalīfah, so that you may return as you once were for ages, kings of the earth and knights of war ... Come O Muslims to your honor, to your victory. By Allah, if you disbelieve in democracy, secularism, nationalism, as well as all the other garbage and ideas from the west, and rush to your religion and creed, then by Allah, you will own the earth, and the east and west will submit to you. This is the promise of Allah to you. This is the promise of Allah to you."*

I calculated the daily proportion of tweets discussing foreign fighters or travel to Syria posted by accounts located in France, Belgium, Germany, and the U.K. in the month surrounding ISIS's caliphate declaration. Figure 2 shows that after the declaration, discourse on foreign fighters significantly increased among these Twitter users.

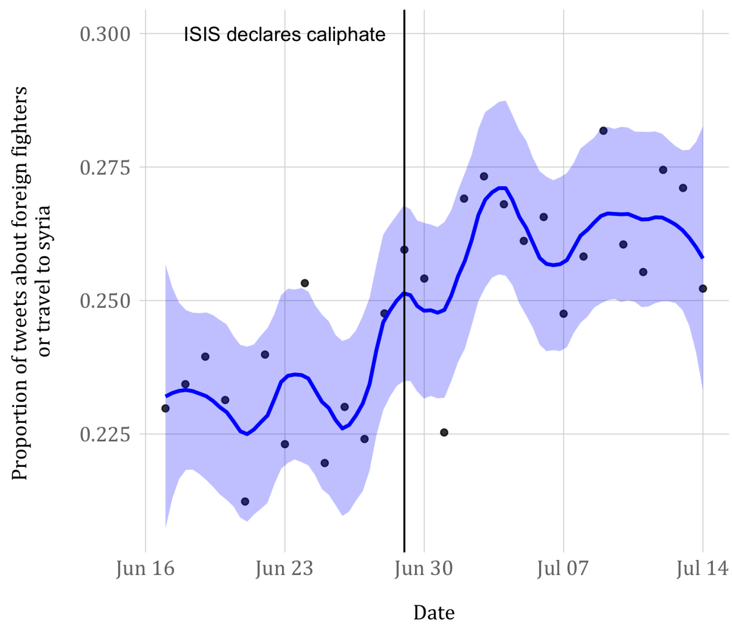
Next, I examine whether online radicalization measures correlate with Western foreign fighter figures. Figure 3 shows a map of ISIS foreign fighters from Europe (Panel A), along with a map showing the number of Twitter users flagged as ISIS activists by @CtrlSec in each country (Panel B). France, the United Kingdom, and Germany have higher numbers of foreign fighters and Twitters users flagged as ISIS activists than many other European countries. Figure 4 displays the correlation between additional online radicalization measures and the number of foreign fighters in the West. It

[18]These data reflect 2014 figures.

[19]Source: `http://myreader.toile-libre.org/uploads/My_53b039f00cb03.pdf`

can be seen that online measures of support for ISIS closely track official foreign fighter counts. While these scatterplots show bivariate relationships, the Supplementary Information provides estimations controlling for population size, which show the same pattern.

Figure 2: ISIS declares caliphate and tweets discussing foreign fighters or travel to Syria

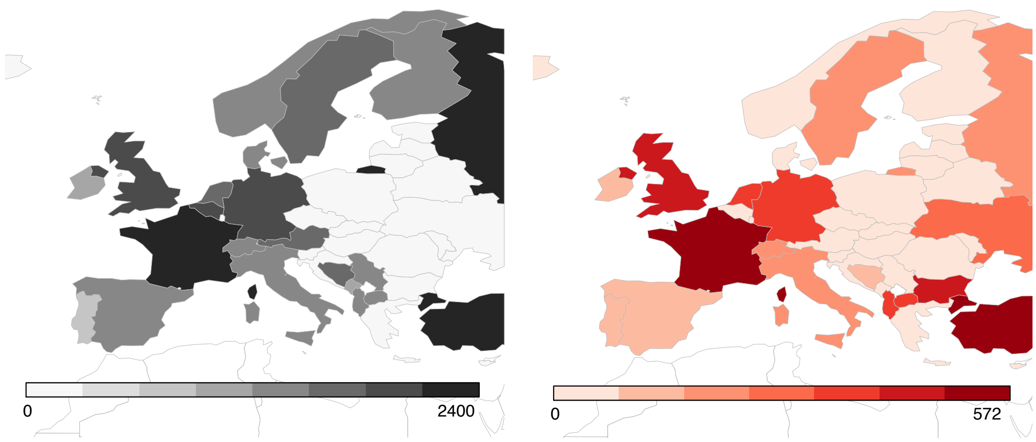


Note: The figure shows the daily proportion of tweets discussing foreign fighters or travel to Syria posted by accounts located in France, Belgium, Germany, and the U.K. in the month surrounding ISIS's caliphate declaration on June 29, 2014. The total number of tweets posted by these users during that month was 27,300, out of which 6,839 were labeled as discussing foreign fighters or travel to Syria.

Figure 3: Foreign fighters and online radicalization in Europe

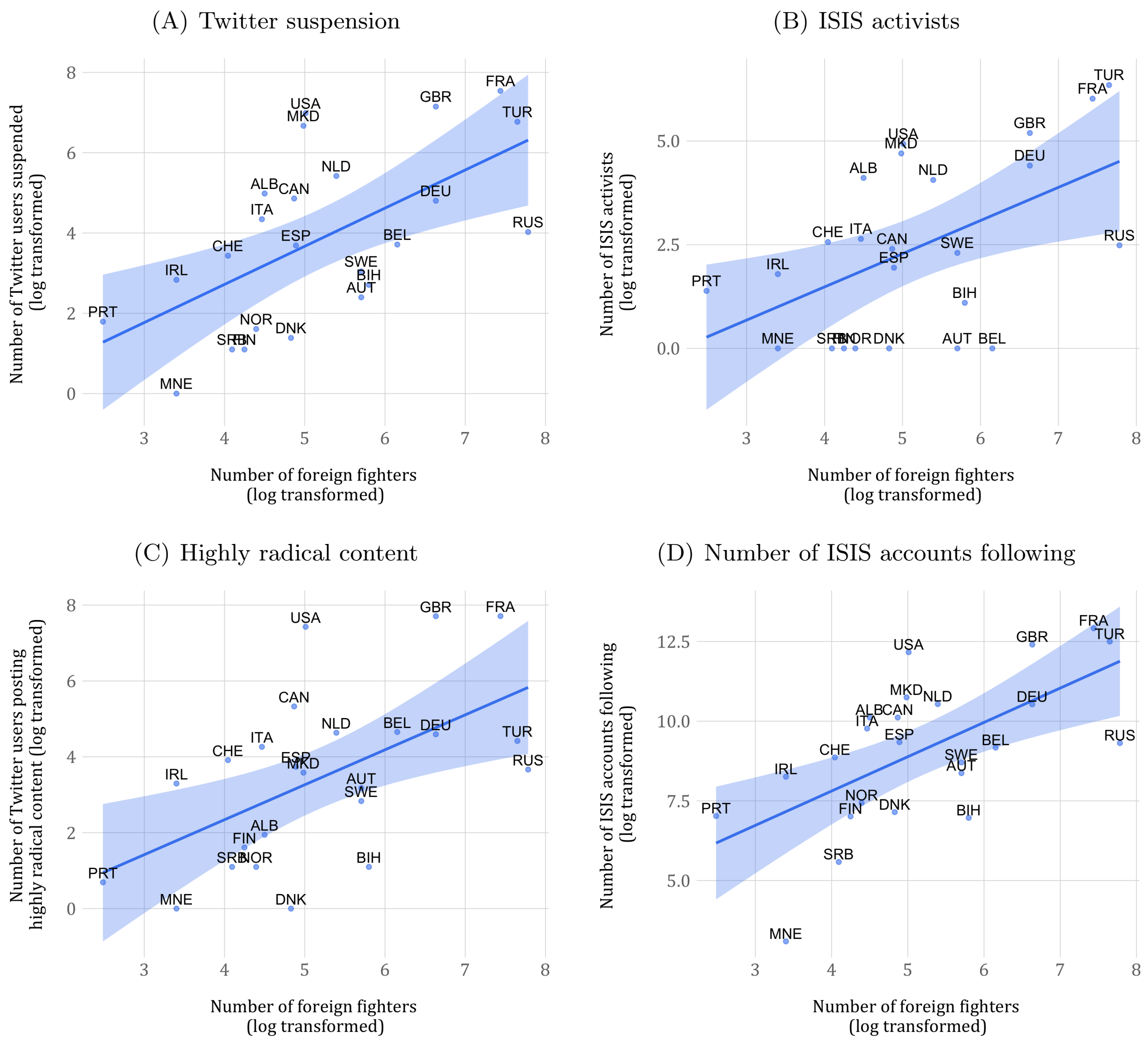
(A) Number of foreign fighters

(B) Number of users flagged as ISIS activists



Note: Panel (A) displays official counts of ISIS foreign fighters in Europe, calculated by Barrett et al. (2015). Panel (B) shows the number of Twitter users flagged as ISIS activist by @CtrlSec, aggregated to the country level.

Figure 4: Foreign fighters and online radicalization (additional measures)



Note: The figure plots scatterplots of the relationship between the number of foreign fighters and online radicalization measures in countries that had at least one foreign fighter with ISIS. Data on foreign fighters are taken from Barrett et al. (2015). Online radicalization measures are based on data collected by the author and are aggregated to the country level. The values are log-transformed.

5 Cross-sectional study

This section examines whether local-level support for far-right parties is linked to greater online support for ISIS. I regress the different online radicalization outcomes on the independent variables described in subsection 3.4 using a combined dataset covering all localities in France, Germany, Belgium, and the United Kingdom. The dependent variables are summarized in Panel A in Table 3 and are measured on the Twitter user level. The independent variables, summarized in Panel B in Table 3, are matched to each individual user in the dataset, but originate in local-level administrative data.[20] I use the following least squares model in my main estimations:

$$Y_{ijk} = \beta_1 V_{ijk} + \beta_2 U_{ijk} + \beta_3 F_{ijk} + \beta_4 P_{ijk} + \beta_5 P_{ijk}^2 + \alpha_k C_k + \varepsilon_{jk} \quad (1)$$

Where i is a Twitter user in geographic area j in country k; Y_{ijk} is one of the online radicalization measures for user i in area j in country k; and V_{ijk} represents the locality-level vote share for far-right parties matched to user i in area j in country k. U_{ijk}, F_{ijk}, and P_{ijk} represent unemployment, share of foreigners, and population size matched to user i in area j in country k, respectively, and C_k is a country fixed effect.[21] The main coefficient of interest in these regressions is β_1, which estimates the relationship between the local-level vote share for far-right parties and online measures of support for ISIS. While this coefficient cannot be interpreted as evidence of a causal relationship, it provides a systematic test of the link between a context of anti-Muslim hostility and online pro-ISIS radicalization.

[20]To account for possible dependency across users in the same area, I cluster the standard errors at the locality level in my main regressions. Since the number of Twitter users in the database is much larger than the number of localities, clustering the standard errors drops 98% of the observations in the standard error calculation. Thus, I report in section S7 in the Supplementary Information materials results without clustered standard errors (but with heteroskedasticity robust standard errors). While these results should be taken with more caution, they are useful for considering relationships with noisy measures or when insufficient clusters, such as with country-by-country regressions.

[21]Data on the share of Muslim populations in each geographical area are only available in the United Kingdom. In estimations with United Kingdom data only, shown below, I find that controlling for Muslim population share does not affect the results.

5.1 Far-right vote share and support for ISIS

Tables 5 and 6 report the main results. In Table 5, Column (1), the dependent variable is a text-based measure that is coded 1 for individuals who are at the top 1% of the distribution of posting pro-ISIS content, and 0 otherwise. To ensure that this content-based measure does not classify as 'radicalized' individuals who just post frequently on issues related to Islam, in Column (2) the dependent variable drops tweets about Islam, measuring 'radical content' only with tweets sympathizing with ISIS, describing life under ISIS territories, and discussing foreign fighters, the Syrian war, and anti-West sentiment. Regardless of the measure used, it can be seen that local-level vote share for far-right parties is positively associated with posting large numbers of radical pro-ISIS tweets. In substantive terms, a one percent increase in far-right vote share is associated with a 3% increase in the probability of being among the top 1% of posters of extremist content.

Columns (3) - (5) in Table 5 report the results when the dependent variable is measured as being flagged by @CtrlSec as an ISIS activist, being suspended from Twitter for association with the organization, and with a count measure of the number of ISIS accounts that a user follows. Here, as well, the results show that vote share for far-right parties is positively related to these radicalization outcomes. However, suspension and number of ISIS accounts followed are not statistically significant at conventional levels with the clustered standard errors specification, although results are significant when estimating the models without clustered standard errors (see Table S21 in the Supplementary Information materials). In substantive terms, vote share for far-right parties is associated with a 6% increase in the probability of being flagged as an ISIS activist.

Table 6 reports the results when the dependent variables reflect the number of tweets posted by a user across all six content outcomes. Here, a one percent increase in the vote share for far-right parties is positively and statistically significantly associated with increases in the number of tweets sympathizing with ISIS, relating to the life in ISIS-controlled territories, discussing the Syrian civil war, expressing anti-West sentiment, and reflecting faith in Islam. Substantively, these reflect an average increase of 4,000-9,000 pro-ISIS tweets across the entire sample. Note that these measures are calculated from content generated in English, Arabic, French, and German, and are measured across thousands of individuals in four countries. The consistency of the results across these text-based measures suggests that this association did not occur by random chance.

5.2 Other correlates of online radicalization

Next, I investigate other correlates of online radicalization. As can be seen in Tables 5 and 6, the unemployment rate at the local level is not robustly associated with online support for ISIS. While content-based outcomes are positively and significantly related to local-level unemployment (see Table 6), they are negatively related to unemployment when the dependent variable is measured as being flagged as an ISIS activist, being suspended from Twitter, or the number of ISIS accounts followed. To investigate whether local-level immigrant unemployment might drive online support for ISIS, I estimate regressions with a variable capturing the percent of unemployed immigrants in a locality in Table 7. Here, as well, results show that the share of unemployed immigrants is not significantly related to online radicalization.

In addition, I examine whether support for ISIS on Twitter relates to the share of foreigners or non-citizens in a locality. The third row in Tables 5 and 6 shows that a greater number of foreigners in a locality is positively associated with online radicalization, but the relationships are not statistically significant for almost all outcomes. In addition, I examine in Table 8 whether the share of refugees in a locality relates to greater support for ISIS on Twitter. I find that the share of asylum seeker and/or asylum seeker centers in a locality is negatively related to being flagged as an ISIS activist, being suspended from Twitter, and to the number of ISIS accounts followed. This is an important finding in light of recent debates over refugee policy in Europe, as it suggests that online radicalization on Twitter is not systematically related to the number of refugees in a locality.

To examine whether these results might be driven by a common third variable linked to both radicalization and far-right support, I use data on possible omitted variables that are available only in the U.K., such as the share of Muslims, Arabs, Pakistanis, Bangladeshis, and foreign-born in each local area. Table 9 shows that when controlling for these variables, vote share for far-right parties remains strongly correlated with the posting of radical pro-ISIS content on Twitter. The findings also show that the local proportion of Muslims is negatively and significantly correlated with posting pro-ISIS content. This is an important finding in light of recent debates on Muslim populations in the West, as it casts doubt on the argument that areas with larger Muslim populations are more likely to be prone to jihadi radicalization.

Overall, these results are consistent with the hypothesis that exposure to anti-Muslim animosity, measured as the local-level vote share for far-right parties, might lead individuals to radicalize and support the Islamic State on social media. The results hold across various dependent variables, in a large number of locations in four European countries. However, since the findings are based on cross-sectional comparisons, it is possible that these relationships are driven by reverse causality—i.e., that the presence of radicalized individuals in a locality increases support for far-right parties, and not the other way around. In the remaining parts of the paper, I investigate these relationships using high frequency Twitter data surrounding events that stir anti-Muslim sentiment: the Paris terrorist attacks in November 2015, the Brussels terrorist attacks in March 2016, and the PEGIDA anti-Muslim marches in February 2016.

Table 5: Far-right vote share and support for ISIS on Twitter

	(1) Indicator for top 1% radical content	(2) Indicator for top 1% radical content, without Islam	(3) Flagged as an ISIS activist	(4) Suspended from Twitter	(5) Number of ISIS accounts following
Far-right vote share (%)	0.25**	0.25**	0.30**	0.09	86.48
	(0.12)	(0.12)	(0.14)	(0.39)	(82.92)
Unemployment (%)	0.20	0.18	-0.20	-1.24*	-111.71
	(0.25)	(0.25)	(0.52)	(0.69)	(140.11)
Foreigners (%)	0.10	0.11	0.26*	-0.06	84.01
	(0.10)	(0.09)	(0.15)	(0.32)	(69.89)
Constant	8.57*	7.68*	-9.76	35.07**	1116.19
	(4.56)	(4.42)	(6.34)	(15.24)	(3729.04)
Population controls	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓
R^2	0.0003	0.0003	0.0062	0.0023	0.0062
Number of clusters	2,655	2,655	2,655	2,654	2,654
Number of observations	112,254	112,254	112,254	112,250	112,250

Robust standard errors in parentheses, clustered at the locality level. Base category is Belgium.

All coefficients are × 1,000 to account for the skewed distribution of the dependent variables.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Far-right vote share and posting pro-ISIS content on Twitter

	(1) Sympathy with ISIS	(2) Life in ISIS territories	(3) Travel to Syria or foreign fighters	(4) Syrian war	(5) Anti-West	(6) Islam
Far-right vote share (%)	0.05**	0.07**	0.07**	0.04**	0.04*	0.08*
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.05)
Unemployment (%)	0.12**	0.14*	0.16**	0.11**	0.13**	0.23**
	(0.05)	(0.07)	(0.08)	(0.04)	(0.05)	(0.11)
Foreigners (%)	0.02	0.02	0.03	0.02	0.02	0.04
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)
Constant	3.51***	5.53***	5.66***	2.68***	3.22***	7.49***
	(0.99)	(1.54)	(1.44)	(0.79)	(0.91)	(1.93)
Population controls	✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓
R^2	0.002	0.005	0.003	0.003	0.003	0.001
Number of clusters	2,655	2,655	2,655	2,655	2,655	2,655
Number of observations	112,254	112,254	112,254	112,254	112,254	112,254

Robust standard errors in parentheses, clustered at the locality level. Base country is Belgium.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Unemployed immigrants and support for ISIS on Twitter

	(1) Indicator for top 1% radical content	(2) Indicator for top 1% radical content, without Islam	(3) Flagged as an ISIS activist	(4) Suspended from Twitter	(5) Number of ISIS accounts following
Unemployed immigrants (%)	0.09	0.11	0.30	-0.47	177.55
	(0.45)	(0.43)	(0.92)	(1.65)	(590.10)
Constant	14.89***	14.38***	0.43	26.64***	3990.51***
	(2.42)	(2.21)	(1.90)	(5.27)	(1327.63)
Population controls	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓
R^2	0.0001	0.0001	0.003	0.001	0.001
Number of clusters	1,318	1,318	1,318	1,318	1,318
Number of observations	90,516	90,516	90,516	90,514	90,514

Robust standard errors in parentheses, clustered at the locality level. Base category is Belgium.

All coefficients are × 1,000 to account for the skewed distribution of the dependent variables.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Asylum seekers and support for ISIS on Twitter

	(1) Indicator for top 1% radical content	(2) Indicator for top 1% radical content, without Islam	(3) Flagged as an ISIS activist	(4) Suspended from Twitter	(5) Number of ISIS accounts following
Asylum seekers (%, sd units)	0.12	0.07	-5.04**	-4.03	-675.54***
	(0.72)	(0.77)	(2.48)	(2.85)	(258.70)
Constant	5.96**	5.34**	14.12	50.98***	6852.84***
	(2.42)	(2.37)	(10.92)	(11.39)	(2384.48)
Controls	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓
R^2	0.0001	0.0001	0.005	0.001	0.001
Number of clusters	1,209	1,209	1,209	1,209	1,209
Number of observations	88,388	88,388	88,388	88,386	88,386

Robust standard errors in parentheses, clustered at the locality level. Base category is Germany.

All coefficients are × 1,000 to account for the skewed distribution of the dependent variables.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Socioeconomic correlates of posting pro-ISIS content on Twitter, United Kingdom, with additional controls

	(1) Sympathy with ISIS	(2) Life in ISIS territories	(3) Travel to Syria or foreign fighters	(4) Syrian war	(5) Anti-West
Far-right vote share (%)	0.06***	0.10***	0.09***	0.05***	0.04***
	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)
Muslims (%)	-0.06**	-0.11**	-0.09**	-0.05**	-0.06**
	(0.03)	(0.05)	(0.04)	(0.02)	(0.02)
Males (%)	-0.04	-0.09	-0.10	-0.04	-0.05
	(0.04)	(0.07)	(0.07)	(0.03)	(0.04)
Pakistanis (%)	0.03	0.07*	0.06	0.03	0.03
	(0.02)	(0.04)	(0.04)	(0.02)	(0.02)
Bangladeshis (%)	0.00	0.04	0.01	0.02	0.01
	(0.02)	(0.04)	(0.04)	(0.02)	(0.02)
Arabs (%)	0.08	0.15	0.12	0.06	0.06
	(0.07)	(0.12)	(0.11)	(0.06)	(0.06)
Foreigners (%)	0.01	0.02	0.03*	0.01*	0.01*
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Unemployment (%)	-0.04	-0.07	-0.08	-0.03	-0.03
	(0.04)	(0.07)	(0.06)	(0.03)	(0.03)
Population	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Population^2	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	2.17	4.25	4.97	2.36	2.68
	(2.34)	(3.79)	(3.67)	(1.76)	(2.03)
R^2	0.001	0.001	0.001	0.001	0.001
Observations	61,925	61,925	61,925	61,925	61,925

Heteroskedasticity robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 High frequency event studies

The relationship between anti-Muslim hostility and pro-ISIS radicalization is complex, and likely runs in both directions. On one hand, anti-Muslim hostility might drive Muslim individuals to radicalize; on the other, radicalization, which in some cases results in violence and terrorism, can increase support for anti-Muslim, far-right parties. To further investigate how anti-Muslim hostility might drive radicalization and support for ISIS on social media, I take advantage of the high frequency nature of Twitter data and examine whether events that stir anti-Muslim sentiment increase online radicalization among potential ISIS recruits. This subsection therefore adds to the prior analysis by studying changes in radical pro-ISIS content over time.

In next subsections I describe these events. First, I consider whether the terrorist attacks in Paris (11/13/2015) and Brussels (3/22/2016) by ISIS-affiliated perpetrators affected radical pro-ISIS content in all localities in France, Germany, Belgium, and the United Kingdom. Second, I evaluate how an anti-Muslim event, the Patriotic Europeans Against the Islamization of the West (PEGIDA) movement's marches across Europe on February 6, 2016, may have led to greater online support for ISIS. As the two event studies reflect the same empirical design, I describe the estimations and results for both studies together.

6.1 Terrorist attacks

Terrorist attacks perpetrated by individuals associated with radical organizations are thought to increase anti-Muslim sentiment and violence in the West (Panagopoulos, 2006; Hanes and Machin, 2014). After 9/11, hate crimes against Muslims increased ten-fold in the United States (Gould and Klor, 2014). Anti-Muslim hostility also grew in Europe after recent terrorist attacks (Healy, 2015). The rise in anti-Muslim sentiment has benefited far-right parties in Europe: several polls conducted after the November 2015 attacks in Paris have shown that support for the far-right Front National party has substantially increased across France (Dearden, 2015; Todd, 2015). Following the Brussels attacks in March 2016, support on social media for the Belgian right-wing Vlaams Belang party increased 30-fold (Sykes, 2016).[22]

I examine whether the Paris attacks of November 2015[23] and the Brussels attacks of March 2016[24] were immediately followed by increased radical, pro-ISIS content among Islamic State supporters on Twitter. The estimations and results are described below. One caveat with studying terrorist attacks, however, is that they might directly inspire radicalization. Individuals sympathetic to the Islamic State might feel inspired and emboldened by a 'successful' terrorist attack. This might lead to increased support for ISIS independent of anti-Muslim hostility. Thus, it is difficult to determine whether increases in radicalization following a terrorist attack are driven by anti-Muslim sentiment. For this reason, as described in the following section, I also examine an event that is likely to increase radicalization only through the anti-Muslim channel: the PEGIDA movement's marches across Europe in February 2016.

6.2 Anti-Muslim marches

The Patriotic Europeans Against the Islamization of the West (PEGIDA) movement was established in Dresden, Germany in October 2014 to oppose immigration, especially from Muslim-majority countries. On February 6, 2016, PEGIDA organized large marches in multiple cities in Germany, Britain, France, Netherlands, Austria, Ireland, Poland, Czech Republic, and Slovakia, to protest against the "Islamization of Europe" (Reuters, 2016). The marches drew thousands who came to express their opposition to the arrival of millions of migrants from Middle Eastern and North African countries, and to warn about Europe "being overrun by Muslims" (Reuters, 2016). This was the largest event organized by the movement so far (Meyer and Storck, 2015; *The Telegraph*, 2016).

The PEGIDA marches provide a useful event for testing the link between hostility against Muslims and pro-ISIS radicalization for two reasons. First, unlike terrorist attacks, which could have

[22]In a related paper, currently in progress, I show that terrorist attacks in Western countries perpetrated by individuals identifying with radical Islamic organizations increase anti-Muslim rhetoric and support for the ideology of far-right parties in a large panel of social media users (Mitts, 2016).

[23]On November 13, 2015, several perpetrators identified with the Islamic State launched several attacks in Paris, including suicide bombings and mass shootings. The attacks killed 130 people and injured hundreds of others, becoming the deadliest atrocities in France since the Second World War. Several polls conducted after the attacks have shown that support for the far-right Front National party has substantially increased across France (Dearden, 2015; Todd, 2015).

[24]On March 22, 2016, ISIS-affiliated suicide bombers detonated explosive devices in Brussels Airport and at a train station nearby, killing 32 civilians and injuring over three hundred. After the attack, support on Facebook for the Belgian right-wing Vlaams Belang party increased by about three thousand percent (Sykes, 2016).

directly inspired radicalization, the anti-Muslim marches were likely to have affected radicalization only through the anti-Muslim channel. Second, since the marches did not provide any *new* evidence on the security threats of radicalized Muslims, they were unlikely to substantially change preexisting attitudes and increase anti-Muslim hostility in areas with low anti-Muslim sentiment. This contrasts with acts of terrorism, which have been shown to increase fear and anti-Muslim attitudes across the population as a whole (Huddy et al., 2005; Sides and Gross, 2013). In many places where the PEGIDA marches took place, counter-protesters gathered to oppose PEGIDA's positions (Huggler and Burgess, 2015; *RT News*, 2016). The marches can therefore be viewed as a "salience test"—an event that stirs emotions, but unlikely to dramatically change preexisting attitudes.[25]

This implies different hypotheses about the effects of the terrorist attacks and the PEGIDA marches on radicalization across localities. First, the terrorist attacks should increase radicalization in general: both in areas that support far-right positions and areas that do not. On the other hand, the impact of the PEGIDA marches should be heterogeneous: radicalization should increase only in areas that already have high levels of anti-Muslim sentiment. In the following subsections, I describe the estimation and results, respectively, for both of these studies.

6.3 Estimation

I estimate several Difference-in-Differences models to study both of these events, where I examine whether the difference in the number of pro-ISIS tweets 1-4 days after the event is larger in areas that have higher vote-share for far-right parties. To be sure, the terrorist attacks and the anti-Muslim marches were events that were discussed on national media to which everyone was likely exposed. The goal of this analysis is to examine whether changes in radical, pro-ISIS content after the events systematically varied between locations with low and high support for far-right parties. A 'pro-ISIS tweet' is coded 1 if its predicted value of belonging to any one of the six content categories—sympathy with ISIS, life in ISIS territories, travel to Syria or foreign fighters, Syrian war, anti-West, or Islam—is above the mean of the predicted values for that category, and 0 if not.

[25] One caveat of studying the marches is that they were planned in advance, and were not a 'surprise' in time. Thus, it is important to not interpret the timing of the marches as exogenous. Nonetheless, the PEGIDA marches likely created an atmosphere where prior sentiment about Muslims became more salient, allowing the examination of variation across space in subsequent radicalization.

For each event, I estimate the following least squares model:

$$Y_{ijk} = \beta_1 T_i + \beta_2 V_{ijk} + \beta_3 (T_i \times V_{ijk}) + \boldsymbol{\delta} \mathbf{X}_{ijk} + \alpha_k C_k + \varepsilon_{jk} \tag{2}$$

Where Y_{ijk} represents the level of radical content in tweet i posted in area j and country k, T_i is an indicator coded 1 for tweets appearing after the event (Paris attacks, Brussels attacks, and PEGIDA marches) and 0 if before, V_{ijk} is the locality-level vote share for far-right parties in area j in country k, $\mathbf{X}_{ijk}$ represents other independent variables described in equation (1), C_k represents country fixed effects, and ε_{jk} are standard errors clustered at the locality level.

6.4 Results

Tables 10 and 11 present the results for the Paris and Brussels terrorist attacks. In both tables, Column (1) uses data on tweets posted one day before and one day after the events; Column (2) uses data from two days before and after, and so forth. Panel A reports the change in the number of pro-ISIS tweets for the sample as a whole. It can be seen that in the first few days after the terrorist attacks in Paris and Brussels the number of radical tweets increased.

Panel B reports the results with the interaction between far-right vote share and the timing of the event. Results show that the difference between areas with low and high support for far-right parties is not statistically significant in most estimations. This pattern can be clearly seen in Figure 5, which plots the difference in the frequency of pro-ISIS tweets after the attack for areas with different levels of far-right vote share. The relatively flat line indicates that radical content increased in a similar manner across all localities in France, Germany, Belgium, and the United Kingdom, regardless of the levels of far-right vote share.

A different pattern can be seen for the anti-Muslim PEGIDA marches. Table 12 and Figure 6 show that the frequency of pro-ISIS tweets changed differently in areas with low and high support for far-right parties. While pro-ISIS content did not increase in areas with low far-right vote share after the PEGIDA marches, it significantly increased in areas with high far-right support. Figure 6 shows a sharp positive slope, where the frequency of pro-ISIS tweets significantly increased after the marches in areas with 30% far-right vote share or more. Figure 7 plots this pattern from data at the hourly level, showing the hourly proportion of pro-ISIS content produced by ISIS sympathizers in the three days before and after the PEGIDA marches. Here too, it can be seen that pro-ISIS content increased in areas with high levels of far-right support, but did not change in areas where far-right parties were not popular. While these results do not provide direct evidence that anti-Muslim hostility is responsible for the increase in pro-ISIS tweets in areas with high support for far-right parties, the results are consistent with the hypothesis that anti-Muslim animosity at the local level, expressed in support for far-right, anti-immigrant and anti-Muslim parties in Europe, increases online support for the Islamic State among potential sympathizers.

Table 10: The Paris attacks and pro-ISIS radicalization

	(1) [-1,+1]	(2) [-2,+2]	(3) [-3,+3]	(4) [-4,+4]
A. Changes in pro-ISIS radical content (standard deviation units)				
After attack = 1	0.160***	0.056***	0.044***	0.043***
	(0.022)	(0.011)	(0.011)	(0.008)
Far-right vote share (%)	-0.001	-0.001	-0.001	-0.000
	(0.003)	(0.001)	(0.001)	(0.001)
Constant	0.065	0.700***	0.741***	0.726***
	(0.148)	(0.058)	(0.058)	(0.052)
Controls	✓	✓	✓	✓
R^2	0.013	0.010	0.007	0.006
Number of clusters	268	327	362	386
Number of observations	9,150	15,223	21,459	27,637
B. Changes in radical content (standard deviation units), by far-right support				
After attack = 1	0.069**	0.086**	0.043	0.061**
	(0.031)	(0.036)	(0.035)	(0.027)
Far-right vote share (%)	-0.006*	-0.003	-0.004	-0.002
	(0.004)	(0.003)	(0.003)	(0.002)
After attack = 1 × Far-right vote share (%)	0.007***	0.002	0.004*	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.160	0.107	0.213*	0.169
	(0.148)	(0.121)	(0.122)	(0.108)
Controls	✓	✓	✓	✓
R^2	0.014	0.011	0.007	0.007
Number of clusters	268	327	362	386
Number of observations	9,150	15,223	21,459	27,637

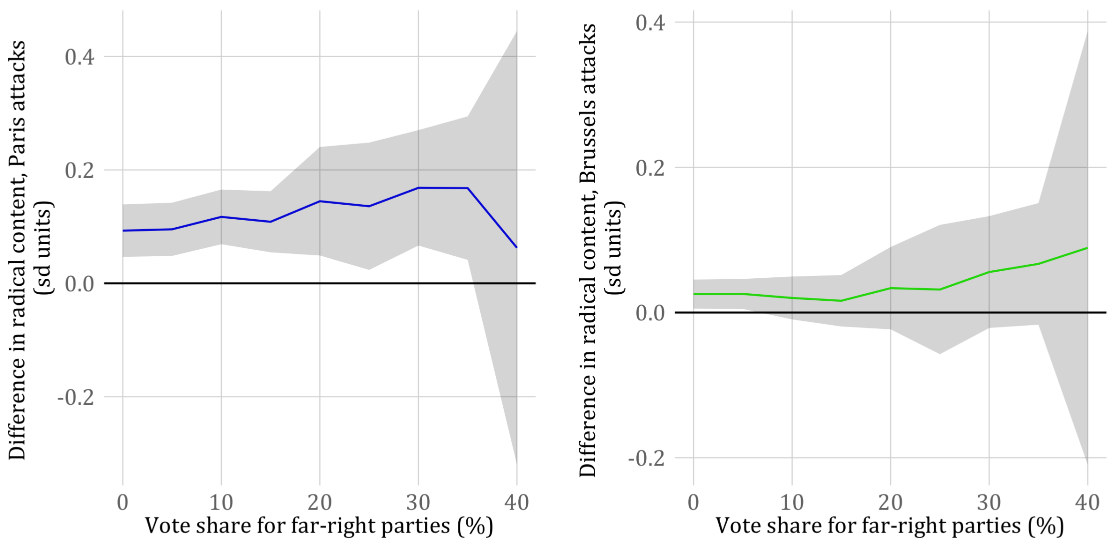
Note: Column (1) uses data on tweets posted one day before and one day after the events; column (2) uses data from two days before and after, and so forth.
Robust standard errors in parentheses, clustered at the locality level.
All coefficients are standardized.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: The Brussels attack and pro-ISIS radicalization

	(1) [-1,+1]	(2) [-2,+2]	(3) [-3,+3]	(4) [-4,+4]
A. Changes in pro-ISIS radical content (standard deviation units)				
After attack = 1	0.037***	0.049***	0.025**	0.013
	(0.014)	(0.013)	(0.010)	(0.009)
Far-right vote share (%)	0.002	0.002	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.113	0.037	-0.001	0.019
	(0.102)	(0.082)	(0.076)	(0.077)
Controls	✓	✓	✓	✓
R^2	0.002	0.003	0.002	0.002
Number of clusters	392	472	529	571
Number of observations	17,613	32,164	46,460	60,773
B. Changes in radical content (standard deviation units), by far-right support				
After attack = 1	0.051**	0.058**	0.025	0.007
	(0.026)	(0.025)	(0.017)	(0.015)
Far-right vote share (%)	0.003	0.002	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
After attack = 1 × Far-right vote share (%)	-0.001	-0.001	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Constant	0.103	0.029	-0.001	0.022
	(0.105)	(0.085)	(0.077)	(0.077)
Controls	✓	✓	✓	✓
R^2	0.002	0.003	0.002	0.002
Number of clusters	392	472	529	571
Number of observations	17,613	32,164	46,460	60,773

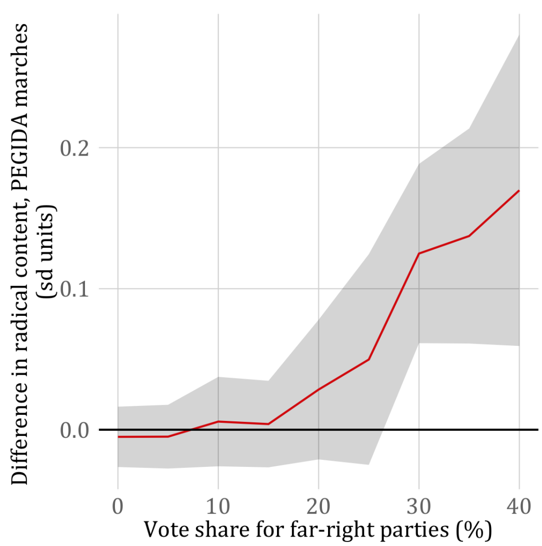
Note: Column (1) uses data on tweets posted one day before and one day after the events; column (2) uses data from two days before and after, and so forth.
Robust standard errors in parentheses, clustered at the locality level.
All coefficients are standardized.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: The Paris and Brussels terrorist attacks and pro-ISIS radicalization, by vote-share for far-right parties



Note: The figure plots the difference in the frequency of pro-ISIS tweets after terrorist attacks for areas with different levels of far-right vote share. The differences are reported in standard deviation units. The left panel reports the results for the Paris attacks; the right panel shows the results for the Brussels attacks. Pro-ISIS content increased in a similar manner across all localities, regardless of the levels of far-right vote share.

Figure 6: The PEGIDA marches and pro-ISIS radicalization, by vote-share for far-right parties



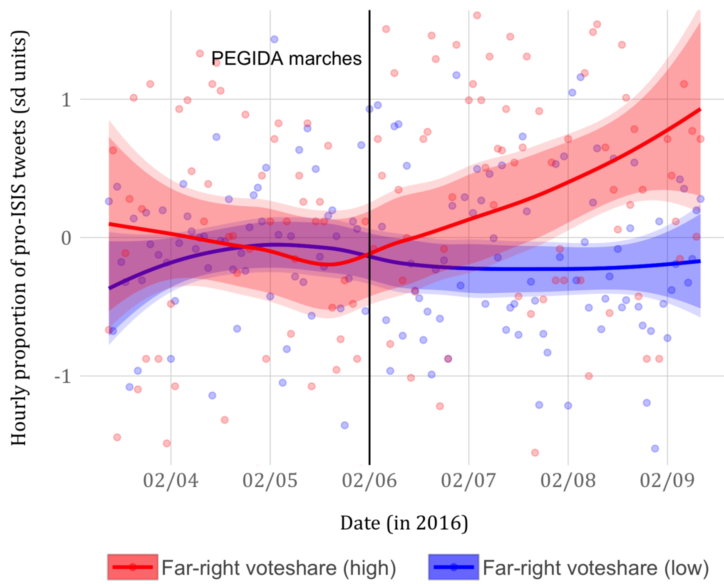
Note: The figure plots the difference in the frequency of pro-ISIS tweets after the PEGIDA marches for areas with different levels of far-right vote share. The differences are reported in standard deviation units. Pro-ISIS content significantly increased after the marches in areas with 30% far-right vote share or more, but did not change in areas with low support for far-right parties.

Table 12: The PEGIDA marches and pro-ISIS radicalization

	(1) [-1,+1]	(2) [-2,+2]	(3) [-3,+3]	(4) [-4,+4]
A. Changes in radical content (standard deviation units)				
After PEGIDA marches = 1	-0.005	-0.012	-0.005	-0.009
	(0.020)	(0.012)	(0.011)	(0.008)
Far-right vote share (%)	-0.002	-0.000	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Constant	0.242**	0.090	0.135	0.143*
	(0.112)	(0.095)	(0.094)	(0.082)
Controls	✓	✓	✓	✓
R^2	0.003	0.002	0.002	0.002
Number of clusters	354	444	508	551
Number of observations	12,305	25,145	38,527	52,636
B. Changes in radical content (standard deviation units), by far-right support				
After PEGIDA marches = 1	-0.036	-0.044***	-0.038***	-0.028**
	(0.022)	(0.016)	(0.014)	(0.011)
Far-right vote share (%)	-0.003	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)
After PEGIDA marches = 1 × Far-right vote share (%)	0.002	0.002*	0.002**	0.001*
	(0.002)	(0.001)	(0.001)	(0.001)
Constant	0.257**	0.103	0.149	0.151*
	(0.111)	(0.094)	(0.094)	(0.082)
Controls	✓	✓	✓	✓
R^2	0.003	0.002	0.002	0.002
Number of clusters	354	444	508	551
Number of observations	12,305	25,145	38,527	52,636

Note: Column (1) uses data on tweets posted one day before and one day after the events; column (2) uses data from two days before and after, and so forth.
Robust standard errors in parentheses, clustered at the locality level.
All coefficients are standardized.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 7: The PEGIDA marches and pro-ISIS radicalization, by the hour



Note: The figure plots the proportion of pro-ISIS content produced by ISIS sympathizers in France, Germany, Belgium, and the United Kingdom (in standard deviation units) at the hourly level, in the three days before and after the PEGIDA marches. The red (blue) dots indicate content produced by individuals located in areas at the top (bottom) 10% of the voting for far-right parties. The bands mark 90% and 95% confidence intervals.

7 Conclusion

This study seeks to shed light on what drives so many to support the Islamic State in the West. By collecting data on thousands of Twitter accounts associated with ISIS, classifying millions of tweets along various dimensions of ISIS support, and mapping Twitter users to geographic locations in France, Germany, Belgium, and the United Kingdom, I showed that Twitter users located in areas that voted for far-right, anti-Muslim parties were more likely to show signs of radicalization than others in less hostile areas. While some have noted there might be a link between the rise of far-right parties and support for ISIS in Europe (Van Zeller, 2016), this paper has provided the first systematic, rigorous study of this proposition.

The findings stress the importance of understanding the process of radicalization and support for extremist movements in the age of social media. The ability to directly reach potential recruits on the Internet, interact with them through social media, and persuade them to embrace extremist ideology is changing how we think about recruitment in subnational conflicts. As the Internet and mobile technology continue to spread across the world, online radicalization is likely to continue, given the ongoing conflicts in the Middle East, North Africa, and other parts of the world. Studying how the online and offline worlds interact in this setting suggests that hostility in one's offline world might lead to the consumption of online radical content.

Looking forward, research on radicalization would benefit from more localized studies aiming to causally identify the mechanisms by which anti-Muslim hostility is linked to online support for ISIS. Does an environment of anti-Muslim hostility increase online support for the Islamic State through a process of identity-seeking? Or is it driven by lack of opportunity to integrate into the surrounding society, e.g., by finding employment or increasing social status? Future work can also examine whether the patterns found in this paper are driven by individuals who are already ISIS sympathizers and, as a result of experiencing hostility, become more vocal in their support, or whether it is driven by the more moderate individuals who are pushed to radicalize after experiencing hostility. In addition, future work could study the determinants of ISIS radicalization in non-Western countries. While some of the same mechanisms might be at play, initial descriptive evidence suggests that recruits' motivations, as well as ISIS's recruitment strategy might be different in non-European countries (Wilson, 2015; Raghavan, 2016).

Finally, future studies might examine ways to de-radicalize potential recruits. With the rise of Islamic State recruitment on social media, several government agencies around the world have attempted to to counter ISIS messages online. While policy efforts such as the State Department's "Think Again Turn Away" campaign have had limited impact (Fernandez, 2015), other, more local and offline de-radicalization efforts have reportedly been more successful in this and prior conflicts (Rabasa et al., 2010; Horgan, 2015). Better understanding of the process that leads individuals to sympathize with a foreign rebel group and radicalize could guide policymakers in identifying effective solutions to combat this troubling phenomenon.

References

Abdo, Geneive. 2006. *Mecca and Main Street: Muslim Life in America after 9/11: Muslim Life in America after 9/11.* Oxford University Press, USA.

Adida, Claire L, David D Laitin and Marie-Anne Valfort. 2014. "Muslims in France: identifying a discriminatory equilibrium." *Journal of Population Economics* 27(4):1039–1086.

Adida, Claire L., David D. Laitin and Marie-Anne Valfort. 2016. *Why Muslim Integration Fails in Christian-Heritage Societies.* Harvard University Press.

Backstrom, Lars, Eric Sun and Cameron Marlow. 2010. Find me if you can: improving geographical prediction with social and spatial proximity. In *Proceedings of the 19th international conference on World wide web.* ACM pp. 61–70.

Barrett, Richard, Jack Berger, Lila Ghosh, Daniel Schoenfeld, Mohamed el Shawesh, Patrick M Skinner, Susan Sim and Ali Soufan. 2015. "Foreign fighters: An updated assessment of the flow of foreign fighters into Syria and Iraq." *The Soufan Group* 4.

Bass, Loretta. 2014. "What Motivates European Youth to Join ISIS?" *Syria Comment* .

Bayman, Daniel and Jeremy Shapiro. 2014. "Be Afraid. Be A Little Afraid: The Threat of Terrorism from Western Foreign Fighters in Syria and Iraq." *Foreign Policy at Brookings* .

Berger, J and Jonathan Morgan. 2015. "The ISIS Twitter Census: Defining and describing the population of ISIS supporters on Twitter." *The Brookings Project on US Relations with the Islamic World* 3:20.

Berger, JM. 2015. "The Metronome of Apocalyptic Time: Social Media as Carrier Wave for Millenarian Contagion." *Perspectives on Terrorism* 9(4).

Biggs, Michael and Steven Knauss. 2012. "Explaining membership in the British National Party: A multilevel analysis of contact and threat." *European Sociological Review* 28(5):633–646.

Borum, Randy. 2011. "Radicalization into violent extremism I: A review of social science theories." *Journal of Strategic Security* 4(4):7.

Bryan, Jennifer. 2005. "Constructing "the true Islam" in hostile times: The Impact of 9/11 on Arab Muslims in Jersey City." *Wounded city: The social impact of* 9(11):133–162.

Burrows, Thomas. 2016. "Islamophobic hate crimes in London have nearly doubled in the last two years as Muslims say they are 'very conscious of keeping your head down'." The Daily Mail. **URL:** *http://www.dailymail.co.uk/news/article-3358535/Islamophobic-hate-crimes-London-nearly-doubled-two-years-Muslims-say-conscious-keeping-head-down.html*

Carter, Joseph A, Shiraz Maher and Peter R Neumann. 2014. *# Greenbirds: Measuring Importance and Influence in Syrian Foreign Fighter Networks.* The International Centre For the Study of Radicalisation and Political Violence.

Chatfield, Akemi Takeoka, Christopher G Reddick and Uuf Brajawidagda. 2015. Tweeting propaganda, radicalization and recruitment: Islamic state supporters multi-sided twitter networks. In *Proceedings of the 16th Annual International Conference on Digital Government Research.* ACM pp. 239–249.

Crossett, Chuck and J Spitaletta. 2010. "Radicalization: Relevant psychological and sociological concepts." *The John Hopkins University* .

Dalgaard-Nielsen, Anja. 2010. "Violent radicalization in Europe: What we know and what we do not know." *Studies in Conflict & Terrorism* 33(9):797–814.

Dancygier, Rafaela M and David D Laitin. 2014. "Immigration into Europe: Economic discrimination, violence, and public policy." *Annual Review of Political Science* 17:43–64.

Dearden, Lizzie. 2015. "Paris attacks: Support rising for far-right Front National as immigration backlash continues." *The Independent.*
URL: *http://www.independent.co.uk/news/world/europe/paris-attacks-support-rising-for-far-right-front-national-as-immigration-backlash-continues-a6745186.html*

ESS Round 7. 2014. "European Social Survey Round 7 Data (2014). Data file edition 2.1." NSD - Norwegian Centre for Research Data, Norway âĂŞ Data Archive and distributor of ESS data for ESS ERIC.

Fernandez, Alberto M. 2015. "Here to stay and growing: Combating ISIS propaganda networks." *The Brookings Project on U.S. Relations with the Islamic World U.S.-Islamic World Forum Papers 2015* .

Flaig, Joseph. 2016. "Khola Hasan from Theydon Garnon says she has experienced increased Islamophobia in Epping Forest." The Guardian.
URL: *http://www.guardian-series.co.uk/news/14459448.Anti_Muslim_media_causing_Islamophobic_attacks_*

Friedman, Jerome, Trevor Hastie and Robert Tibshirani. 2010. "Regularization Paths for Generalized Linear Models via Coordinate Descent." *Journal of Statistical Software* 33(1):1–22.
URL: *http://www.jstatsoft.org/v33/i01/*

Front National. 2016. "The National Front Platform.".
URL: *http://www.frontnational.com/le-projet-de-marine-le-pen/*

Goldenberg, Jacob and Moshe Levy. 2009. "Distance is not dead: Social interaction and geographical distance in the internet era." *arXiv preprint arXiv:0906.3202* .

Golder, Matthew. 2016. "Far Right Parties in Europe." *Annual Review of Political Science* 19(1).

Gould, Eric D and Esteban F Klor. 2014. "The Long-Run Effect of 9/11: Terrorism, Backlash, and the Assimilation of Muslim Immigrants in the West." *The Economic Journal* .

Grant, Madeline. 2014. "16% of French Citizens Support ISIS, Poll Finds." Newsweek.
URL: *http://www.newsweek.com/16-french-citizens-support-isis-poll-finds-266795*

Greenberg, Karen J. 2016. "Case by Case: ISIS Prosecutions in the United States." *Center on National Security, Fordham University School of Law* .

Grimmer, Justin and Brandon M Stewart. 2013. "Text as data: The promise and pitfalls of automatic content analysis methods for political texts." *Political Analysis* 21(3):267–297.

Hainmueller, Jens and Daniel J Hopkins. 2014. "Public attitudes toward immigration." *Annual Review of Political Science* 17.

Hall, Ellie. 2015. "Gone Girl: An Interview With An American In ISIS." *Buzzfeed News.*
URL: *https://www.buzzfeed.com/ellievhall/gone-girl-an-interview-with-an-american-in-isis?utm_term=.grBaBZdyN#.iv22gLK9N*

Hanes, Emma and Stephen Machin. 2014. "Hate crime in the wake of terror attacks: Evidence from 7/7 and 9/11." *Journal of Contemporary Criminal Justice* .

Healy, Blathnaid. 2015. "Far-right parties gain popularity in Europe after Paris attacks." Mashable.
URL: *http://mashable.com/2015/01/14/far-right-europe-paris-attacks/#w2HcIBkWV8qH*

Homeland Security Committee. 2015. "Final Report of the Task Force on Combating Terrorist and Foreign Fighter Travel.".

Horgan, John G. 2015. "De-radicalization programs offer hope in countering terrorism.".
URL: *http://www.latimes.com/opinion/op-ed/la-oe-0215-horgan-terrorist-deradicalization-20150215-story.html*

Huddy, Leonie, Stanley Feldman, Charles Taber and Gallya Lahav. 2005. "Threat, anxiety, and support of antiterrorism policies." *American journal of political science* 49(3):593–608.

Huggler, Justin and Richard Burgess. 2015. "Germany's 'Islamisation' marches: how the pro- and anti-Pegida rallies measured up." The Telegraph.
URL: *http://www.telegraph.co.uk/news/worldnews/europe/germany/11342953/Germanys-Islamisation-marches-how-the-pro-and-anti-Pegida-rallies-measured-up.html*

Inge, Sophie. 2013. "Nazi graffiti and pig's head left at mosque site." The Local.
URL: *http://www.thelocal.fr/20130415/nazi-graffiti-and-pigs-head-found-on-mosque-site*

Isaac, Mike. 2016. "Twitter Steps Up Efforts to Thwart Terrorists' Tweets." New York Times.
URL: *http://www.nytimes.com/2016/02/06/technology/twitter-account-suspensions-terrorism.html*

James, Gareth, Daniela Witten, Trevor Hastie and Robert Tibshirani. 2013. *An introduction to statistical learning.* Vol. 112 Springer.

Jurgens, David. 2013. "That's What Friends Are For: Inferring Location in Online Social Media Platforms Based on Social Relationships." *ICWSM* 13:273–282.

Jurgens, David, Tyler Finethy, James McCorriston, Yi Tian Xu and Derek Ruths. 2015. Geolocation Prediction in Twitter Using Social Networks: A Critical Analysis and Review of Current Practice. In *Proceedings of the 9th International AAAI Conference on Weblogs and Social Media (ICWSM).*

Kent Online. 2015. "MP Gareth Johnson contacts police over Britain First "anti-halal operation" in Dartford." Kend Online.
URL: *http://www.kentonline.co.uk/dartford/news/mp-contacts-police-over-far-right-38953/*

King, Gary and Langche Zeng. 2001. "Logistic regression in rare events data." *Political analysis* 9(2):137–163.

Klausen, Jytte. 2015. "Tweeting the jihad: Social media networks of Western foreign fighters in Syria and Iraq." *Studies in Conflict & Terrorism* 38(1):1–22.

Lubbers, Marcel and Peer Scheepers. 2002. "French Front National voting: a micro and macro perspective." *Ethnic and Racial Studies* 25(1):120–149.

Lyons-Padilla, Sarah, Michele J Gelfand, Hedieh Mirahmadi, Mehreen Farooq and Marieke van Egmond. 2015. "Belonging nowhere: Marginalization & radicalization risk among Muslim immigrants." *Behavioral Science & Policy* 1(2):1–12.

Marans, Daniel. 2015. "What You Need To Know About Syrian Refugees Who Have 'Positive' Views Of ISIS." Thw World Post.
URL: *http://www.huffingtonpost.com/entry/syrian-refugees-positive-views-isis_us_564e2c72e4b08c74b734fc83*

McCauley, Clark and Sophia Moskalenko. 2008. "Mechanisms of political radicalization: Pathways toward terrorism." *Terrorism and political violence* 20(3):415–433.

McGee, Jeffrey, James A Caverlee and Zhiyuan Cheng. 2011. A geographic study of tie strength in social media. In *Proceedings of the 20th ACM international conference on Information and knowledge management*. ACM pp. 2333–2336.

McGee, Jeffrey, James Caverlee and Zhiyuan Cheng. 2013. Location prediction in social media based on tie strength. In *Proceedings of the 22nd ACM international conference on Conference on information & knowledge management*. ACM pp. 459–468.

Meyer, Henning and Ulrich Storck. 2015. "Understanding Pegida – An Introduction.".
URL: *https://www.socialeurope.eu/wp-content/uploads/2015/03/Pegida-eBook.pdf*

Mitts, Tamar. 2016. "Transnational Terrorism and Anti-Muslim Sentiment in the West: A Social Media Analysis." *Columbia University* .

Mousseau, Michael. 2011. "Urban poverty and support for Islamist terror: Survey results of Muslims in fourteen countries." *Journal of Peace Research* 48(1):35–47.

Norris, Pippa. 2005. *Radical right: Voters and parties in the electoral market*. Cambridge University Press.

Nussio, Enzo. 2017. "The Role of Sensation Seeking in Violent Armed Group Participation.".

Office for National Statistics. 2016. "Super Output Area (SOA).".
URL: *http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/census/super-output-areas–soas-/index.html*

Panagopoulos, Costas. 2006. "The polls-trends Arab and Muslim Americans and Islam in the aftermath of 9/11." *Public Opinion Quarterly* 70(4):608–624.

Pooley, Elizabeth. 2015. A New Sisterhood: The Allure of ISIS in Syria For Young Muslim Women in the UK PhD thesis Arizona State University.

Rabasa, Angel, Stacie L Pettyjohn, Jeremy J Ghez and Christopher Boucek. 2010. "Deradicalizing Islamist Extremists." *DTIC Document* .

Raghavan, Sudarsan. 2016. "Two of her daughters joined ISIS. Now she's trying to save her two younger girls." The Washington Post.
URL: *https://www.washingtonpost.com/world/middle_east/two-of-her-daughters-joined-isis-now-shes-trying-to-save-her-two-younger-girls/2016/05/25/700ea478-1d1e-11e6-82c2-a7dcb313287d_story.html*

Reuters. 2016. "Anti-Islam movement PEGIDA stages protests across Europe." Reuters.
URL: *http://www.reuters.com/article/us-europe-migrants-protests-germany-idUSKCN0VF0P4*

Robinson, Belinda. 2015. "ISIS supporter, 17, is sentenced to 11 years in prison for tweeting 7,000 messages backing the terror group and helping a friend to join fighters in Syria." Daily Mail.
URL: *http://www.dailymail.co.uk/news/article-3214436/Virginia-teenager-ran-pro-ISIS-Twitter-account-sentenced-11-years-prison.html*

RT News. 2016. "Dozens arrested as Pegida anti-migrant marches sweep across Europe." RT News.
URL: *https://www.rt.com/news/331586-pegida-anti-migrant-demonstrations-europe/*

Rydgren, Jens. 2008. "Immigration sceptics, xenophobes or racists? Radical right-wing voting in six West European countries." *European Journal of Political Research* 47(6):737–765.

Schmitt, Eric and Somini Sengupta. 2015. "Thousands Enter Syria to Join ISIS Despite Global Efforts." New York Times.
URL: *http://www.nytimes.com/2015/09/27/world/middleeast/thousands-enter-syria-to-join-isis-despite-global-efforts.html*

Sedgwick, Mark. 2010. "The concept of radicalization as a source of confusion." *Terrorism and Political Violence* 22(4):479–494.

Shane, Scott, Matt Apuzzo and Eric Schmitt. 2015. "Americans Attracted to ISIS Find an 'Echo Chamber' on Social Media." International New York Times.
URL: *http://www.nytimes.com/2015/12/09/us/americans-attracted-to-isis-find-an-echo-chamber-on-social-media.html?_r=0*

Sides, John and Kimberly Gross. 2013. "Stereotypes of Muslims and Support for the War on Terror." *The Journal of Politics* 75(03):583–598.

Stack, Liam. 2015. "American Muslims Under Attack." New York Times.
URL: *http://www.nytimes.com/interactive/2015/12/22/us/Crimes-Against-Muslim-Americans.html?_r=0*

Sykes, Selina. 2016. "Far-right support surges in Belgium as anger grows over Brussels terror attacks." Express.
URL: *http://www.express.co.uk/news/world/655822/Brussels-attacks-Belgium-far-right-Flemish-parties-nationalist-Flanders-independence*

Takhteyev, Yuri, Anatoliy Gruzd and Barry Wellman. 2012. "Geography of Twitter networks." *Social networks* 34(1):73–81.

The Telegraph. 2016. "Thousands march in anti-Islam Pegida rallies across Europe." The Telegraph.
URL: *http://www.telegraph.co.uk/news/worldnews/europe/germany/12144357/Thousands-march-in-anti-Islam-Pegida-rallies-across-Europe.html*

Todd, Tony. 2015. "French far-right sees popularity rise after Paris attacks." France 24.
URL: *http://www.france24.com/en/20151123-french-far-right-popularity-attacks-paris*

Van Zeller, Mariana. 2016. "Radicals Rising." Fusion.
URL: *http://interactive.fusion.net/radicals-rising/*

Vidino, Lorenzo and Seamus Hughes. 2015. "ISIS in America: From Retweets to Raqqa (George Washington University: Program on Extremism, 2015) 7.".

Wiktorowicz, Quintan. 2005. *Radical Islam rising: Muslim extremism in the West*. Rowman & Littlefield Publishers.

Wilner, Alex S and Claire-Jehanne Dubouloz. 2010. "Homegrown terrorism and transformative learning: an interdisciplinary approach to understanding radicalization." *Global Change, Peace & Security* 22(1):33–51.

Wilson, Lydia. 2015. "What I Discovered From Interviewing Imprisoned ISIS Fighters." The Nation. **URL:** *http://www.thenation.com/article/what-i-discovered-from-interviewing-isis-prisoners/*