Global Terrorism and (De-)Mobilization: Do Islamic State’s Deadly Attacks Disengage, Deter, or Mobilize Supporters?

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Abstract

What are the consequences of committing violent attacks for terrorist organizations? Terrorist attacks might broaden the base of supporters by increasing the perceived group efficacy. However, terrorist attacks might also lead its supporters to believe that the organization is excessively violent or involvement may become too dangerous. This paper employs a unique dataset with 300,842 observations of 13,321 Twitter accounts linked to the Islamic State (IS), collected during a 127-day period, to empirically investigate the impact of terrorist attacks on the number of the organization’s supporters. By exploiting the exogenous timing of terrorist attacks as a natural experiment, we find that the number of followers of IS-related Twitter accounts significantly reduces in the aftermath of the attacks. Additionally, we empirically disentangle two mechanisms: disengagement—a change in supporters’ beliefs—and deterrence—de-mobilization due to fear. Because we do not find support for the latter, we conclude that the disengagement effect dominates our main result.

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What are the consequences of committing violent attacks for the terrorist organizations? In the end, do they attract more supporters? Scholars and pundits alike generally refer to the existence of two opposing effects in their description of the consequences of violent terrorist activity: a mobilization effect and a disengagement effect. On the one hand, attacks may aim at solidifying and broadening the base of supporters within the terrorist organization (Acosta, 2014b; Doosje et al., 2016). On the other hand, attacks are also a tool to show their capacity and infuse terror among the populace. While this effect targets the general population, they may also have effects on those who were already supporters. Specifically, terrorist attacks might lead supporters to believe that the organization is excessively violent or involvement may become too dangerous, which might lead to a decrease in the number of terrorist supporters (Doosje et al., 2016; Moghadam, 2012). In this paper, we provide systematic evidence for the effect of terrorist attacks on the number of supporters in the context of the Islamic State (IS). We contribute to the empirical literature of terrorism by providing an answer about which effect dominates among those segments of the population that are on the cusp of being outsiders and insiders regarding a terrorist organization. We do so by exploring the dynamics in those groups relative to IS on their most important communication and recruitment tool: Twitter.

In this paper, we argue that the number of followers of IS-linked Twitter accounts reveals crucial information about the (de)mobilization dynamics regarding the relationship between terrorist organizations and societies. While we are not able to empirically move beyond the follower-non-follower dichotomy, we provide a useful framework from which to theoretically think about who moves across the insider-outsider boundary when we observe shifts in the overall number of followers. Hence, we begin by providing a theoretical mapping of Twitter followers into three types: 1) organization supporters, such as leaders, active members who unconditionally support the organization, and latent sympathizers; 2) observers, non-supporters who follow IS-linked accounts to acquire information, such as media reporters, or individuals fighting against IS, but who would never support the organization; and, 3) non-followers. The first group are the insiders of the organization in the sense that they have shown a degree of sympathy towards it; the second group—as well as a third group composed of the entire population of Twitter non-followers—constitute the outsiders. Hence, the overall change
in the number of followers before and after an attack reflects three types of effects depending on the type of individuals who move across categories. Terrorist attacks may have: (1) attentional effects, non-followers may become observers; (2) mobilization effects, non-followers may turn into insiders; (3) de-mobilization effect, insiders may become outsiders after an attack either because of a disengagement effect, a change in beliefs leads to a reduction in support, or a deterrence effect, an increase in the fear of being tracked and prosecuted for their links with radical or violent activity. The purpose of this paper is to disentangle these effects in the context of online IS’s supporters.

To test the theoretical inequality of interest, we have implemented an automatic routine that collected the daily reports made by Anonymous on IS-related Twitter accounts and extracted key information on these accounts over 127 days—from March 14 to July 22, 2016. Altogether, we collected information on 300,842 observations, account-date data points, on 13,321 unique Twitter accounts. Then, we merged these with the data on real-world data on terrorist attacks around the world that occurred during our period of study. Using this constructed dataset, we examine whether terrorist attacks linked to IS exert an impact on the number of followers of IS-related accounts by combining observational and quasi-experimental research designs.

Different methodological perspectives provide a strong empirical regularity: IS’ terrorist attacks decrease the number of followers of IS-related Twitter accounts in the aftermath of an attack. The estimated effect regarding Twitter followers is both statistically and quantitatively significant. We employ two empirical strategies with identical conclusions.

First, we test our main hypothesis by using an interrupted time series analysis. In this case, we explore the discontinuous changes in the number of followers around two major attacks in our dataset: the Brussels bombing on 22 March 2016 and the attack in Nice on 14 July 2016. Second, we exploit the panel structure of our dataset to examine the effect of the intensity of a terrorist attack on the number of followers in their accounts using several model specifications, including random and fixed effect models, which exploit only variation in the number of followers within each account. By doing this, we observe that terrorist attacks precede fluctuations over time in the number of followers.

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1For our empirical analysis, we will only be able to use 239,434 account-date observations on 10,554 accounts to ensure the quality of our dataset. For additional details, see the data section below.
in IS’s terrorist attacks; this is true especially for attacks that occurred on European soil as compared to other attacks in Asia and Africa for which the effect is still negative and significant, but smaller in magnitude. Though we detect a surge in the number of accounts that are reported to Twitter for their potential links to IS, our estimated effects of terrorist attacks remain negative and significant after adjusting for such activity. Hence, both analyses consistently point to the negative effect of the attacks on the number of followers of the terrorist organization on Twitter.

Our core finding provides evidence of a de-mobilization effect of terrorist attacks on the followers who support the organization. This effect is particularly strong considering that we only observe the net effect: the de-mobilization effect is discounted for the opposite mobilization and attentional effects. Yet, the de-mobilization effect is not entirely homogeneous but it may consist of two components: the disengagement effect, the action of un-following the organization due to a change in supporters’ beliefs in the aftermath of an attack; and, the deterrence effect, the act of un-following the organization to avoid being tracked after an attack—so, by “going dark”. To evaluate these two distinct mechanisms, we examine whether the de-mobilization effect is, as the deterrence mechanism would suggest, stronger for accounts that are located in countries where governments’ counter-terrorist activities have the capabilities to credibly retaliate against perpetrators, so countries with strong national material capabilities. Instead, we find that the de-mobilization effect of terrorist attacks is not stronger among the sub-sample of accounts that can be geographically located in countries in strong states. Hence, we conclude that the disengagement effect—a change in beliefs—is the most plausible explanation for the de-mobilization effects of terrorism on the organizations’ supporters.

Overall, this paper speaks to several strands of literature. First, we offer a critical theoretical account on the types of effects that terrorist attacks may have on terrorist organization, as well as its relationship to the population. Second, we present novel systematic evidence on the impact of terrorist attacks on the disengagement of probable terrorist supporters. Though there is some prior empirical research on the consequences of terrorism on some relevant political outcomes, including people’s attitudes and ideology (e.g., Peffley, Hutchison and Shamir, 2015) and governmental policies (e.g., Abrahms, 2012), his study contributes further to this research strand by systematically exam-
ining the impact of the use of violence on potential supporters of terrorist organizations. Third, our work contributes to the growing literature that employs big data to answer long-standing questions in political science (e.g., Barberá, 2015; Barberá et al., 2015; ?) by using a novel dataset on IS-related Twitter accounts. In addition, our work connects to the heated debate in political science on whether big data and causal inference are contradictory trends by employing big data in a quasi-experimental framework.

1 Terrorist Attacks: Mobilization, Disengagement and Deterrence

There are several possible explanations for the relationship between terrorist attacks and the size of terrorist organizations. The variation in the activities of terrorist groups may be explained by a number of factors, including the psychology of individual terrorists (e.g., Horgan, 2005; Victoroff and Kruglanski, 2009), adherence to religious ideals (Pargament, Magyar-Russell and Murray-Swank, 2005), socialization processes (Turk, 2004), or their contextual socioeconomic factors (Mitra et al., 2008; Piazza, 2011). In this paper, we focus on the impact of deadly terrorist attacks on reshuffling the supporters of an organization.

An influential view on the purpose of terrorist attacks in political science suggests that terrorist groups use violence either as a costly signal to show strength and capacity (Hoffman and McCormick, 2004; Kydd and Walter, 2006; Siegel and Young, 2009). Though the effectiveness of groups’ strategies is a matter of scholarly debate, terrorist attacks certainly change the political position of the group through the provision of new information about them to either governments, the people or both. Therefore, violent activity provides new information about the effectiveness and objectives of

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2 See, for instance, Abrahms (2008) and (Moghaddam, 2005) for an argument that terrorism sometimes pursue non-instrumental goals.
3 Using all suicide terrorist attacks between 1980 and 2003, Pape (2005) finds that half of the suicide terrorist attacks have achieved some policy concessions with the targeted states, although see Acosta and Childs (2013); Moghadam (2008) for contrary evidence. Also, Abrahms (2012) shows that terrorist attacks are not effective at extracting policy concessions when attacks are targeted to the civilian population.
4 For instance, Kydd and Walter (2006) suggest that groups pursue five goals via the costly signaling of terrorist attacks: attrition, intimidation, provocation, spoiling, and outbidding. Though each goal has distinctive characteristics, all of them share the underlying mechanism of providing new information to either the government, the people or both. In addition, notice that even if some terrorist groups may not have full control over all violent activities on the ground, their execution on behalf of the organization—regardless of the organization’s prior consent—should be sufficient to imply their political and social consequences.
the organization, which may result in two opposed processes: mobilization and de-mobilization.

On the one hand, terrorist attacks may *mobilize* supporters by increasing the perceived group efficacy. Terrorist violence can be seen as a strategic mobilization tool that aims at ensuring a “self-sustaining rate of [political mobilization]” (Acosta, 2014a), solidifying the loyalty of the already militant members, and broadening the base of supporters to ultimately institutionalize the organization (Acosta, 2010, 2014a, 2016; Bueno de Mesquita and Dickson, 2007). In this sense, Doosje et al. (2016) argue that an increase in the levels of perceived group efficacy is a crucial determinant in the micro-level process of radicalization. The declaration of the Islamic States in Iraq and Syria, for instance, arguably increased the perceived capacity of the IS, which helps to explain the large number of foreign fighters who travelled to IS-controlled areas.

On the other hand, not only does the nature of the attacks signal strength to the people to achieve their ends, but it also conveys relevant information to their supporters about the kind of strategies they use, the character of their members, and the goals of the organization (Bueno de Mesquita and Dickson, 2007; Hoffman and McCormick, 2004). The new information about the organizational capabilities, the character, and its goals provided by violent terrorist attacks may backlash and lead to *disengagement*. Some individuals who might have sympathized with the organization in the past may come to realize that they cannot cope with new levels of violence. Though idealistic expectation about the organization may have led some to follow or actively engage in its activities, terrorist acts may lead once-supporters to believe that violence has gone too far.

Qualitative empirical evidence suggests that disengagement may be a common process among members of terrorist organizations. In their work with exit programs in northern Europe, Bjørgo (2011) showed that individuals who belonged to extreme-right movements often exited those organizations because they felt that too much violence. Studies of the determinants that led to a reduction in the number activitists linked to the basque terrorist group *Euskadi Ta Askatasuna* (ETA), Alonso (2011) and Reinares (2011) report evidence showing that many fighters exited the organization because of disagreements with the violent tactics of the organization. In a similar vein, Moghadam’s (2012) in-depth study of the decline of the Red Army Faction revealed that disagreements over tactics
and strategies led to an update of beliefs about the organization that initiated their disengagement with
the organization.

Another driver of behavioral changes after terrorist attacks is deterrence. The perception of
prosecution and surveillance among supporters of terrorist organizations may increase after violent
activity. In this regard, Alonso (2011) report changes in beliefs among members and sympathizers of
ETA in the aftermath of violent attacks due to fear from the attack or successful police prosecution
in its aftermath. However, deterrence is less likely to work in cases where terrorists do not have a
known address (Schmid, 2013). However, the effectiveness of deterrence is not the same across all
countries, but it depends on the credibility of a state to punish and credibly threaten to retaliate against
members of the organization (Wenger and Wilner, 2012). Hence, the credibility to exert deterrence
on terrorists is likely to depend on the national material capabilities of states to allocate resources in
security, defense and intelligence services. In the context of the modern terrorist organization, which
places a great degree of their activity through online tools of communication and recruitment, all users
can potentially be tracked by intelligence services. Consequently, post-attack deterrence processes are
likely to change the behavior of some supporters of the organizations by leading them to go offline out
of fear of being tracked, especially in those countries where intelligence services are more credible to
threaten retaliation.

2 Islamic State in Twitter

An increasing number of terrorist groups make an intensive use of mass media and social media to
disseminate their messages (Rudner, 2017). The availability of these new technologies has made it far
easier to distribute the groups’ films and images: terrorist attacks and violent scenes are reproduced
live uncensored, which has led to an unprecedented stream of online violence. Besides the use of
regular television channels to promote their films in the news, terrorist organizations have begun to
be highly involved in a number of decentralized digital platforms through social media networks like
Twitter or Facebook; peer-to-peer messaging apps like Telegram and Surespot; and, content sharing
systems like JustPaste.it (Clark, 2016). While this has been the case for a large number of terror-
ist organizations worldwide, the Islamic State has intensively used Twitter for both propaganda and recruitment purposes as it offers great technical advantage for the global dissemination of text and image messages (Klausen, 2015). In this regard, FBI Director James Comey argued in July 2015 that IS’s strategy consists in “broadcasting on Twitter, get people to follow them, then move them to Twitter Direct Messaging”. After a short screening of whether the follower is a likely recruit, then “they’ll move them to an encrypted mobile-messaging app so they go dark to us” (Aspen, 2015).

In this paper, we argue that the number of followers of IS-linked Twitter accounts reveals crucial information about the (de)mobilization dynamics regarding the relationship between terrorist organizations and societies. To see how changes in IS-related accounts reflect support of IS, we first classify users into three categories according to their relationship with IS’s Twitter-related accounts: 1) IS’s leader members, fighters, active supporters, and sympathizers; they constitute owners of IS-related accounts and the followers of the IS-related accounts; 2) the observers: the people who do not support, but follow their accounts because they are consumers of IS’s information (e.g., media reporters who follow the latest news in Syria through IS’s Twitter accounts) or people fighting IS; and, 3) the non-followers: they are all other users on Twitter who do not follow and do not support IS’s activities currently, yet all of them could turn into IS’s passive or active supporters in future periods. This group constitutes the vast majority of Twitter users.

Therefore, terrorist attacks are exogenous shocks that reshuffle the number of people in each of the three types of users, which map into the types of movements that we described in the theoretical discussion above. First, mobilization effects occur when a non-follower becomes an explicit supporter of the organization by following it on some of their related accounts. In a second place, attentional effects define aggregate movements of observers toward IS-related Twitter accounts; they are non-followers who begin following their accounts with the simple purpose of obtaining first-hand information on the organization and their activities (e.g., media reporters), yet they have no chance of becoming supporters of the organization. If terrorist attacks either generate mobilization and/or

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5We acknowledge that movements may occur within the boundaries of the organization. This is the case if, for instance, attacks encourage some sympathizers to become fighters. Though potentially relevant, within-group processes go unobserved in our empirical strategy and, thus, we limit our theoretical discussion to the movements across group boundaries.
attentional effects, then we should expect an increase in the number of followers after deadly IS’s terrorist attacks. This leads to the following hypothesis:

**Hypothesis 1.1 (mobilization and/or attention hypothesis):** *Terrorist attacks increase the number of followers on IS-related accounts.*

As we theoretically discussed above, terrorist attacks may also de-mobilize supporters via disengagement or deterrence. On the one hand, some supporters may update their beliefs over the organization and may realize that the organization does not fulfill their desires, so they withdraw their support from the organization and un-follow IS-related accounts. In addition, some previous IS’s followers may stop to follow IS-related accounts not because they change their preferences or beliefs out of fear of being tracked and associated with terrorist organizations. If either effect or both are at work after terrorist attacks, then we should expect a decrease in the number of followers after deadly IS’s terrorist attacks. These effects lead to the following hypothesis:

**Hypothesis 1.2 (de-mobilization hypothesis):** *Terrorist attacks decrease the number of followers on IS-related accounts.*

The nature of the treatment analyzed in this paper—deadly terrorist attacks—should not be interpreted as the attacks alone, but we should conceptualize it in a broader sense. To the discrete event of the attack, the actual treatment includes the entire causal chain that a terrorist attack triggers, including reactions to the attack by other citizens, media, politicians, institutional figures, and the like. Hence, this compounded treatment is obviously larger as the salience of the attack is greater. In brief, it is reasonable to expect that attacks that produce a larger number of deaths and geographically located in Western countries are both providing a more costly signal and generating greater international turmoil, we should expect that if the attacks are the actual treatment in our empirical findings, then these two indicators should be influencing the changes in the number of supporters to the organization. In sum, the logic of the heterogeneous strength of the attacks rises the following empirical expectation:

**Hypothesis 2 (salience hypothesis):** *Terrorist attacks influence the number of followers on IS-related accounts, especially after attacks in Western countries.*
In addition to establishing the net effect of terrorist attacks on the number of followers, we can tease out the logic behind a potential de-mobilization effect to explore its mechanisms, disengagement and deterrence, by exploiting heterogeneity in our results. The crucial distinction between disengagement and deterrence is whether the change in individuals’ behavior is the result of learning from the attacks and, thus, a shift in beliefs; or, the consequence of fear or threat of online or offline prosecution. Though we do not have data to directly observe neither of these two mechanisms, we lay out a key empirical observation for the deterrence effect, and then subject it to empirical examination.

According to the deterrence effect, terrorist attacks increase the beliefs among followers that their behavior may become noticeable and tracked by security agencies, which leads to a change in behavior but in beliefs. In the context if IS in Twitter, IS’s supporters may become dark on Twitter by un-following IS-related accounts after a terrorist attack, which would explain a potential decrease in the average number of supporters. Yet, if the deterrence effect dominates our negative result, then we should observe that those followers located in countries with a more credible threat to prosecute or retaliate against online activists, so countries with greater national material capabilities, should be more likely to drop from following IS-related accounts in the aftermath of an attack. Testing this hypothesis means testing for the relevance of the deterrence over the disengagement mechanism conditional on finding a negative effect in our main hypotheses.

**Hypothesis 3 (conditional on de-mobilization: deterrence hypothesis):**

*The number of followers on IS-related accounts decreases after a terrorist attack, especially among accounts located in countries with stronger national material capabilities.*

### 3 Data Extraction on IS-related Accounts

The data used in this paper were obtained by following “the reports” of the anti-IS Twitter bots set up by the international hacker initiative *Anonymous*. This hacker group declared cyberwar on IS almost immediately after the IS attack in Paris on November 13, 2015. After that horrible event, the anti-IS initiative started to work in multiple directions, one of which was to report IS-related accounts in Twitter.
This paper makes use of 300,843 reports from the anti-IS Anonymous bots collected over the period from 03/16/2016 to 07/20/2016. Each report is a Twitter account. Most of the accounts in this data set have been reported multiple times and eventually got suspended (hence, there is a clear life-cycle of the accounts in the sample: they were reported the first time, then they were reported a couple of more times, then they were suspended). Each time when a certain Twitter account was reported, its profile information was collected. The gathered data is an unbalanced panel, in which \( n \) is a reported Twitter account and \( t \) is the date of this report. Overall, the final dataset has information on 13,321 unique accounts.\(^6\)

Crucially for our analysis, each entity in the data contains information on the number of followers, date of the report, language of the account, time-zone, and the number of friends, favorites and statuses on each reported account for every time the account was reported.\(^7\) Our dependent variable is the number of followers in an account in date \( t \).

To test our third hypothesis, we generate a variable that takes into account the capacity of the state in which the account is located to credibly threaten to prosecute or retaliate against online activists. We measure a country’s material capabilities to credibly prosecute perpetrators and to retaliate using the National Material Capabilities (version 5) (Singer, Bremer and Stuckey, 1972). Ideally, we would predict the exact country in which an account is located and, then, match it to a country’s capabilities to retaliate. While we lack information to precisely geo-locate the accounts with their profile information,\(^8\) We employ a supervised machine learning algorithm to train an ordinal regression model using the Two-Class Boosted Decision Tree model and generate five clusters of accounts based on the resources to retaliate by the country in which an account is located, using the characteristics of the accounts for which we have complete information.

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\(^6\)We clean the raw dataset before using it for our analysis. Specifically, our final sample for analysis excludes observations that have extreme activity rates. Accounts with a high ratio of following accounts over followed accounts are likely to be bots, and accounts with a low ratio of following accounts over followed accounts are likely to be media. Because they may behave differently than regular accounts and their behavior may be too influential for our results, we have chosen to exclude the lowest and the highest decile. Our final sample size is, thus, 239,434 user-date from 10,554 accounts. While trimming the dataset on the extremes aims at cleaning the data of extreme observations, the findings presented in this paper are the same if we include all of the observations.

\(^7\)The raw data collection process was performed using a couple of specific Python scripts running on a remote server and gathering information 24/7. Then, the data refinement and aggregation was performed on a stand-alone machine via a C# .Net application in Visual Studio 2015; the application was developed particularly for this project.

\(^8\)In our sample database, only 12% of the accounts provide self-described geographic information.
An alternative approach would be to use the wealth of probabilistic and machine learning techniques that claim to accurately geo-infer the location of Twitter users accounts (Cheng, Caverlee and Lee, 2010; Compton, Jurgens and Allen, 2014; Jurgens, 2013; Rout et al., 2013). Social network-based geo-inference relies on evidence suggesting that relationships in social media strongly indicate real-world spatial proximity across users (Gonzalez et al., 2011). Whereas some political scientists have begun to use it (Mitts, 2017), there are two caveats that prevent us from using them for the task of geo-inferring the location of IS-related accounts. First, the current evidence suggesting that user’s online network is a strong predictor of a user’s offline geographic location is based on samples of ordinary citizens. However, Islamic State is an international social network of sympathizers and supporters. Therefore, an important feature is the international character of its user’s social network (e.g., Berger, 2015; Byman, 2016). Consequently, the assumption that online networks reflect offline networks in the context of transnational digital organizations is not yet supported by empirical evidence. Second, even if we accepted that online networks reflect their offline network among users with IS-related accounts, the prediction error for most methods to infer geolocation show that these methods are still under development as they still yield mean and median prediction errors that are too imprecise for country-level geolocation, most range between about 200km to 8000km (for a comparison of methods, see Jurgens et al. (2015)).

Overall, rather than predicting an account’s geographic location, which is prone to both systematic and random measurement error, we predict the strength of the state in which an account is located, its NMC score, based only on the account’s profile information. This technique generates predicted NMC scores with low prediction errors.9

3.1 The Cumulative Lagged Measure of Terrorist Attacks

We complement the information extracted from the accounts reported by Anonymous with data on daily terrorist incidents linked to IS. An incident is included in our dataset if an authoritative figure, such as a country’s president or vice-president, addresses the nation by stating or strongly suggesting that an attack is committed by the IS. In the absence of direct information from a governmental

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9See online Appendix D for further details on our algorithm and its predictive power.
authoritative figure, we include episodes that have been connected to IS by reliable media sources within a few hours of the attacks. Notice that the inclusion criterion of a case depends on the general perception of the attack in the immediate aftermath of the attack, as opposed to the result of formal investigations.\textsuperscript{10}

Hypothesis 2 reflects the idea that the effect of attacks on (de)mobilization are greater as the general impact of the attack is larger. As argued earlier, this impact factor may be related to two components: the number of casualties and the location of the incident. For this reason, we construct two independent variables for each day in our period taking into account these two parameters. Firstly, we compute the number of deaths from terrorist attacks linked to IS that occurred in the United States and Europe. Secondly, we do the same for the number of deaths outside the United States and Europe. Hence, our independent variables do not reflect just whether there is an attack on a particular day, but they weight each attack for the number of deaths that it generates, and differentiate between those in Europe and the US and elsewhere. If our empirical strategy reflects our theoretical reasoning, then we should observe that the effect of the number of victims in the US and Europe should be larger than the effect of casualties located geographically elsewhere.\textsuperscript{11}

However, the assumption of an instant effect of a terrorist attack lasting only one day is unrealistic. Hence, a smoothing temporal approach for effect is a logical decision. Indeed, media coverage and news stories linger for some days after an attack. Consequently, we should expect to observe the consequences of an attack on the same day of the attack and over its immediate aftermath, although, probably, decreasing in magnitude. For this reason, we have chosen to implement a smoothing decreasing curve after the shock by applying a discount factor of 50\%, 75\%, and 100\% to the number of deaths. For each day in our dataset, we compute the cumulative mortality parameter, $c_{dt}$; it aggregates all previous deaths from the terrorist attacks with a discount factor:

\textsuperscript{10}See online Appendix B for a list of all terrorist incidents included in our analysis.\textsuperscript{11}There are no attacks in the US in our dataset, although we include a mention to the US throughout the paper because we would have included attacks in the US in a separate category with Europe. In addition, we refer to attacks in European soil to those attacks within our period that occurred in Belgium, France, Germany, and Turkey. However, if we exclude Turkey from this category, the results for the variable of attacks in Europe become even stronger.
\[ cd_t = \sum_{i=1}^{I} deaths(i) I(t \geq t(i)) \left( 1 + r \right)^{(t - t(i))}, \]

where \( i \) is a terrorist attack on day \( t(i) \) and \( deaths(i) \) is the number of deaths it caused; \( r \) is the discount rate applied, and \( (t - t(i)) \) is the number of days since the incident. This is summed for all incidents before \( t \). In the online Appendix C, we estimate the cumulative death parameter around the Brussels bombings on March 22, 2016, with \( r=0.5 \), to show that our selected discount rate parallels the changes in the keywords “Brussels bombing” reported by Google Trends.\(^{12}\)

To illustrate the incidence of violence linked to IS within our period of study, Figure 1 reports the cumulative lagged measure of deaths from terrorist attacks linked to IS from our initial extraction date (03/16/2016) to the end of the data collection period (07/20/2016). Altogether, there are two major attacks in European soil: on 22nd March in Brussels, Belgium; and on 14th July in Nice, France.\(^{13}\) Outside European soil: the major attack was the two coordinated bomb attacks in the Karrada district in Baghdad, Iraq, on the 3rd of July, with over 300 deaths.

[Figure 1 about here]

4 Empirical Strategy

Exploiting the temporal variation in terrorist attacks throughout our period of study, we use a pre-post approach to estimate their effects on the number of followers in the IS-related Twitter accounts. More specifically, for account \( a \) on day \( t \), we estimate the models of the form:

\[ Y_{at} = \beta_0 + \beta_1 cd_t + \alpha_a + \epsilon_{at}, \]

where \( Y_{at} \) denotes the log of followers of account \( a \) on day \( t \). As noted previously, \( cd_t \) is the continuous variable that equals the number of terrorist victims in day \( t \), smoothed with a discount rate of 50%, 75%, or 100%. The parameter of interest in our model equation is \( \beta_1. \)

\(^{12}\)The correlation of Google attention to the event and our cumulative value is above 0.90 within a one-month window around the event. Other attacks in the sample or greater discount rates do not differ in the evolution of the attention over time, but some of them had obviously less overall attention.

\(^{13}\)The attack in the Attaturk airport in lstambul, Turkey, is another attack that is coded as in European soil, although it is unclear whether it should be computed in Europe or outside Europe. Notice, however, that including it in the dataset as Europe or not does not alter any of the results.
Our main specification includes user-account fixed effects ($\alpha_a$). With regards to the plausibility of the identification condition, account fixed-effects are important because there are strong differences across accounts—language, geographic location of the user, demographic characteristics, as well as other observed and unobserved covariates. The major danger of an empirical strategy without account fixed effects is selection bias in the sample before and after an attack. This can arise as a result of shifts in either the type of accounts that Anonymous targets, which may be different in a period before and after an attack, or shifts in the behavior of users, including the opening or closing of accounts. The inclusion of account fixed effects allow us to remove all time-invariant heterogeneity across accounts (e.g., average number of followers throughout the period, language, geographic location) and focus on the average variation within accounts over time.

Another concern that is that the effects we observe may not be driven by changes in the behavior of ISIS’ online audience, but instead they might be a product of the time-variant aggressive account suspension efforts by Twitter and the Anonymous’ hacktivist group in the aftermath of terror attacks. We construct two variables that account for changes in the behavior of Twitter and Anonymous. First, we create a variable that indicates the total number of reports Anonymous sends to Twitter every day. Second, we generate a measure of daily behavioral changes of Twitter that captures the total number of suspended accounts in our dataset. Though they are both post-treatment, they allow us to assess whether our findings are driven by changes in the behavior of Twitter and/or the Anonymous in the aftermath of terrorist attacks.

For the interpretation of the parameter $\beta_1$ as a causal estimate of the effect of terrorist attacks on the number of followers, we need to assume that timing of the terrorist attacks is exogenous to the pre-attack number of followers in Twitter accounts linked to IS. While a violation of the assumption is more likely when using long periods of time, we believe the assumption of the exogenous timing of terrorist attacks is highly plausible, because our sample period is comprised of a short time span of only 127 days. For instance, the likelihood of a terrorist attacks in 2012 may be very different from that of a terrorist attack in 2016 for reasons that we do not fully understand. However, the chance of a terrorist attack in a given day within the 127-day period of our analysis—from 16th March to
20th July, 2016—is likely to be approximately constant within short periods from the perspective of Twitter followers and non-followers. In practical terms, this means that the exact day of the attack is generally not known in advance.

In short, for the causal parameter that we estimate to be biased, not only does it require the chance of an attack to vary over time, but to vary as a function of the number of followers in the periods immediately before an attack, or without an attack.\(^\text{14}\) Thus, the parameter \(\beta_1\) can be interpreted as a causal estimate of the effect of terrorist attacks on the number of followers of IS-related accounts because the uncertainty related to the precise timing and nature of the attack provides an identification mechanism for our empirical tests.

## 5 Results

The results section is divided into three subsections. We first implement an interrupted time series analysis on the two most important attacks in Europe that fall within our time period of study: The Brussels bombing on March 22 and the Nice attack on July 14, both in 2016. This allows us to provide a first empirical evaluation of the relationship by employing a quasi-experimental research design with strong internal validity. Second, we move to the panel data analysis where we combine daily Twitter data with terrorist attacks worldwide during our entire period. This design enables us to generalize the prior findings to all other terrorist events with models that convincingly estimate a causal effect. Finally, we explore the mechanisms of the negative association found in the first two subsections by separating disengagement from deterrence.

### 5.1 An Interrupted Time Series Analysis of Two Major Attacks

To assess the causality of the relationship, we employ an interrupted time series analysis, a type of regression discontinuity design (RDD) in which the running variable is defined by time (Percoco, 2014). The terrorist data and the information on Twitter accounts is ideal for this approach because of the well-defined moment of the attack and the large number of accounts that we have collected in

\(^{14}\text{When we refer to an attack day, we are actually referring to the attack day and a number of days in the aftermath of the attack that are affected by the attack.}\)
every single day throughout our period of analysis, which statistically empowers small bandwidths.

In brief, there is a potential outcome $Y_j$ for each account-observation $j$—the number of followers of an account; a treatment assignment variable $W_j$—observation observed in the pre- or post-treatment period— which determines the potential outcome we eventually observe, so $Y_j(W_j)$, i.e., either $Y_j(1)$ or $Y_j(0)$; a forcing variable $t_j$, which is a running covariate—time to the attack in our case—and, finally, a cutoff value $c$, which establishes the interruption in the time series, which is set at 0 (the attack date in our case). Hence, the treatment assignment is given by:

$$W_j = \begin{cases} 
1 & \text{if } t_j \geq c \\
0 & \text{if } t_j < c 
\end{cases}$$

The primary quantity of interest is the immediate change in the number of followers represented by $\tau$ in the following equation:

$$\text{followers}_j = \alpha + \tau W_j + f(t_j) + \epsilon_j$$

where $\text{followers}_j$ indicates the number of followers in an account-observation, $\alpha$ is an intercept of the model, $\text{Attack}_j$ is an indicator for whether an observation falls in the the day of the attack or later, $f(t_j)$ is a smooth function of the running variable time in days from the day of the attack, which can be positive or negative, and $\epsilon_j$ is an error term. To estimate $f$, we use a non-parametric estimation (local linear regression).

A crucial step in this approach is the decision about the bandwidth, the window period of analysis. In general terms, there is a trade-off between precision and bias. On the one hand, a strategy that uses a large bandwidth would allow us to precisely estimate a causal effect because it would use a large number of observations ranging from many days before and after the attack. Because it allows data points that are far from the attack in the estimation of the outcome in both the control and treated periods, differences across units may arise because they were generated in different environments. On the other hand, we would like to minimize the bias of our estimate by subsetting our temporal focus to a narrow temporal window, and thereby removing those observations that are far from the day of the
attack. Yet, the general downside of this strategy is that we work with a reduced sample size, which reduces the precision of our estimates.

We choose a baseline bandwidth following the parameters suggested by Imbens and Kalyanaraman (2012) (IK) and test the sensitivity of the estimates by using different bandwidths, ranging from that suggested by IK to only one day before and after the attack. In the estimation procedures, we use triangular kernel, as recommended by Lee and Lemieux (2010), which gives more weight to those observations closer to the cutoff point.

5.1.1 Attack on Brussels, Belgium

On 22 March 2016, two blasts hit the main terminal of Zaventem international airport, in the north-east of central Brussels, and another explosion struck the Maelbeek metro station in the area where several European institutions are located. These three coordinated suicide bombings killed thirty-two civilians and three of the perpetrators, and more than 300 people were injured. Shortly after the explosions, IS claimed responsibility for the attacks in a statement released via Twitter, Telegram, and other social media.

To evaluate the impact of the attacks on the number of followers, we subsetted our dataset to only those observations that are observed more than once and fall within the window of 15 days before and after the attack.15 As our data collection procedures were initiated on March 16, the pre-attack period is six days before the attack and the post-attack period is 15 days after the attack.16

Table 1, Panel A, presents the main estimates of the impact of the terrorist attack in Brussels on the number of followers in the accounts linked to IS. Table 1 shows the estimation equation by local linear regression using the number of followers as the dependent variable. Our treatment variable is \( \text{Attack}_i \), so the coefficient \( \tau \) on \( \text{Attack} \) captures the effect on the number of followers of being in the pre-attack period versus the post-attack period, i.e., it measures the effect of crossing the threshold—the attack date, from left to right—on the number of followers.

[Table 1 about here]

---

15 We excluded all observations with the extreme number of followers—the top 1% percentile. However, the results are not driven by these decisions.

16 The decision of choosing a specific time window is not relevant analytically because the bandwidth used is systematically narrower than this time range.
Under this specification, the attack in Brussels decreased the number of followers by 37 followers, which is equivalent to a 9.9% decrease from the mean number of followers of the twelve-day period—six days to the left and six days to the right on the attack’s timeline. Importantly, the estimated negative effect is consistent significantly and quantitatively similar across different bandwidth specifications, whether doubling or halving the IK bandwidth. Moreover, even if we focus on the two-day period centered around the attack day (bandwidth = 1), the effect is also significantly negative. Figure 2a graphically shows the discontinuous jump around the attack date. This provides substantial evidence of the causal impact of the Brussels attack on the number of Twitter users following IS-related accounts.

[Figure 2 about here]

5.1.2 Attack on Nice, France

This subsection explores whether we see a similar effect for the largest terrorist attack on Western soil during our period of study. On the night of July 14, 2016, a man driving a 19-ton refrigerated truck and carrying an automatic pistol deliberately drove into crowds that were celebrating the Bastille Day on the Promenade des Anglais in Nice, France. The attack resulted in the deaths of 86 people and 434 injuries. On the morning of July 15, 2016, a few hours after the attack, the French president, Francois Hollande, addressed the nation in a televised speech, stating that the attack was terrorist in nature and linking it to the Islamic State by saying: “all of France is being menaced by Islamic fundamentalist terrorism.” Further evidence for this explicit link being made by the President was that he also used his televised speech to announce “the strengthening of [...] the actions in Syria and Iraq” (Mestre, Revault d’Allonnes and Bissuel, 2016). On July 16, IS, via its news agency, the Amaq News Agency, claimed responsibility for the attack by stating that a “soldier of the Islamic State” executed “a new, special operation using a truck”, and warning that “no matter how much they enforce their security measures and procedures, it will not stop the mujahideen from striking” (France24, 2016; Williams, 2016).

To evaluate the impact of this attack on the number of followers, we subsetted our dataset to only those observations that are observed more than once and fall within the window of 15 days before and
after the attack, as we did for the Brussels attack. In this case, however, our period of analysis stops a few days after the attack, on 20th July 2016, and, consequently, we have a 15-day pre-treatment period and a 7-day post-treatment period. Given that the bandwidths that we will use are narrower than this time window, this will not affect our estimates.

Table 1, in Panel B, presents the main estimates of the impact of the terrorist attack in Nice on the number of followers in the accounts linked to IS. As we did for the Brussels bombing, our favorite specification is reported in column (3) because it uses the bandwidth suggested by Imbens and Kalyanaraman (2012). Under this specification, the Nice attack decreases the number of followers by 40 followers, which is equivalent to a 15% decrease from the mean number of followers throughout the eight-day period—four days to the left and four days to the right of the attack’s timeline. Additionally, the effect is consistently negative and statistically significant across bandwidths—the IK’s bandwidth, its half, or its double —, although the effect decreases as we incorporate data points that are further apart from the attack date. Interestingly, if we focus on the difference between the date before the attack and the attack date (bandwidth equals 1), the effect is also significantly negative. Figure 2b illustrates the discontinuous jump downwards that occurs between the date before and after the attack. Next, we explore whether these negative effects are consistent with a more general pattern of a causal and negative effect of attacks on the number of followers in accounts associated with IS using all the available data.

5.2 Main Analysis

Table 2 reports the impact of the number of victims in IS attacks on the number of followers of IS in Twitter on the day of the attack and in its immediate aftermath. Panels in the Table show the results across different discount rates. Models 1 and 4 report OLS regression estimates with no user-account fixed effects. Models 2 and 5 report varying-intercept multilevel models where day-intercepts are modeled as a function of attacks perpetrated by IS. Finally, models 3 and 6 include fixed effects at the level of the account. In addition, models 4 through 6 also control for both Anonymous’ daily intensity of its reporting activities and Twitter’s daily intensity of its suspension activities.

17To avoid repetition, this estimates follow the same logic as Panel A for the case of Brussels.
Columns 1 and 2 show that the effect of the number of victims in the US and Europe is negatively related to the log of the number of followers of Twitter-related accounts. However, these models may be biased due to distinct sample composition in the pre-attack and the post-attack periods. Column 3 also reports a significantly negative effect of attacks on followers after focusing on the within-account variation alone. This specification is closest to identifying a causal effect because it incorporates an intercept for each account and, consequently, controls for all between-account heterogeneity. Consistently, IS’s deadly attacks decreases the number of followers in IS-related Twitter accounts. Columns 4 through 6 report the same set of coefficients after controlling for daily changes in the intensity of the reporting activity by Anonymous and the suspending activity by Twitter. The intensity of Anonymous’ reporting activity seems to increase the number of followers and the intensity of the Twitter’s banning activity seems to decrease the number of followers, yet these effects are not consistent across all model specifications and do not substantively alter our main finding.

If these models are capturing a true causal effect of bombing, we should expect that the effect of an extra victim in the United States and Europe should be stronger than the effect of a victim elsewhere. As expected, models in columns 1 through 6 show that the effect of a victim outside Europe and the United States is negative but the magnitude of the effect is significantly smaller than a victim in Europe or the United States. In particular, the effect of an individual death in Europe and the US leads to a decrease in the log of followers in that same day is between $-0.0045$ and $-0.00392$, yet the impact of a victim outside the US and Europe is between $-0.00009$ and $-0.00076$, respectively; that is, 5 times smaller. In other words, a terrorist attack outside Europe and the US requires about 5 deaths to achieve the equivalent effect to a single death within the US or Europe on the number of followers.\footnote{Formally, we can reject the null hypothesis that the coefficients of the victims in US and Europe are the same as the coefficient elsewhere for all 18 models. For instance, OLS, random effects and fixed effects models with controls based on a 50% discount rate have a \( \chi^2 \) statistic of 161.9 ($p-value < 0.001$), 7.2 ($p-value < 0.01$), and 205.6 ($p-value < 0.001$), respectively.}

Altogether, these results empirically support the thesis that the de-mobilization effect from the attacks dominates its mobilization effect since we are able to detect a significant negative effect on the number of followers in the aftermath of these events. While the results are statistically significant,
we now turn to discuss whether the magnitude of the effect is substantive. Certainly, the large size of our sample allows us to detect effects that are very small in magnitude. Therefore, it is pertinent to discuss whether our parameter of interest captures a causal effect that is substantively meaningful. Before moving to the discussion of the magnitude of the effect, we should bear in mind that the estimated parameter does not capture the full impact of de-mobilization, but only the net effect of de-mobilization after subtracting it from a potential mobilization effect. If we assume that both effects may be strictly positive in absolute values, then the estimated de-mobilization effect should be interpreted as a lower bound of its true effect.

Figure 3 reports the predicted value of the number of followers in IS-related Twitter accounts as a function of the number of deaths associated with a particular day in the sample. The number of followers in Twitter accounts related to IS is predicted to be close to 137 if there has not been an attack on that day nor on the dates immediately following. However, an attack in the US or on European soil would imply a decrease in the number of followers in that day and in its aftermath, and this decrease depends on the intensity of and the proximity to the attack. Approximately, each 25 victims leads to an average decrease of 2 followers in their accounts. By contrast, the magnitude of the decrease in the number of followers is much weaker because it requires an attack with 100 deaths to generate a change in the predicted value of 1 follower less in IS’s Twitter accounts.

[Figure 3 about here]

In the interpretation of these results, we should take into account that the variable “number of deaths” does not truly account for the number of victims in a given day because the variable is measured in a way that allows for lingering effects of a given terrorist attack over time. Thus, to explore the actual impact of a discrete attack in the number of followers, we should assess not only the effect it has on a particular day but the cumulative effect it has throughout the period in the aftermath of the attack. To illustrate the shifts in the predicted values as a function of the number of deaths in an attack, Table 3 reports the five bloodiest attacks within our period of study, the date they occurred, their location, their death toll, and the predicted change in the number of followers caused by an attack alone.

[Table 3 about here]
The values in the last column are the predicted cumulative percentage change in the number of followers as a result of actual death toll related to attacks observed within our period of study. As a reminder, this means that the effect of the Brussels bombing had a value of 36 on 22 March 2016, 24 on March 23, 11 on March 24, 3 on March 25, 1 on March 26, and values indistinguishable from 0 thereafter. Hence, the simulation exercise involves summing these actual values in the variables produced by single attacks to obtain the change in the predicted value expected from each discrete attack. The results show that the largest impact was generated by the case of the attack in Nice with an average accumulative change of a 7.5% decrease in the number of followers. Another important impact is caused by an expected 6.6% decrease in the number of followers that would be expected from the Karrada bombings, a coordinated attack that killed 341 people on 3 July 2016 in Baghdad, Iraq. Even though not so important in magnitude, the attack in Istanbul and Brussels killing 44 and 36 people would be expected to cause a 3.8% and 3.2% decrease.

This simulation exercise allows us to illustrate that the magnitude of the effects observed in our models are significant statistically, but also quantitatively. To put these percentages in perspective, a 7% decrease from a starting point of 137 means an average of 9 fewer followers. Taking into account that there are about 10,554 accounts related to IS throughout our period of study, this quantitatively means an expected drop of 94,986 in the absolute number of followings to IS.19 This is a substantial reduction in the size of IS’s Twitter audience. Overall, this finding is entirely consistent with the interrupted time series analysis provided above.

5.3 Exploring the Mechanism: Disengagement or Deterrence?

In this section, we try to tease out the logic behind the negative effect of terrorist attacks on the number of followers on Twitter between the two potential explanations: the disengagement and deterrence effect. We utilize the known geographic location of some accounts to test for the deterrence effect. Hence, if the deterrence effect is the only driver of our main findings, then we should see that the negative effect is significantly larger among those accounts located in countries that can credibly

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19 This does not take into consideration that one user can be counted more than once because it may withdraw from following several posting accounts at the same time. Therefore, this should be interpreted as an upper bound estimate of the average decrease in the number of users.
punish and threaten to retaliate against potential perpetrators of terrorist attacks. We test whether those accounts that are geographically located in countries with strong states, whose material capabilities to allocate resources in security, defense and intelligence services might credibly threaten to retaliate against perpetrators and their supporters, are more likely to decrease their number of followers in the aftermath of attacks.20

To test the empirical prediction of the deterrence mechanism, Table 4 reports four model specifications. Model 1 shows that the effect of 100 European deaths on the log of followers is $-0.382$ for those accounts located in the weakest set of countries, so NMC equals 0, and the coefficient slightly strengthens to $-0.446$ for those located in the strongest set of countries. Yet, the difference in effect is not statistically significant across any of the models. Models 2 also reports a lack of significant moderation after including fixed effects at the level of the account. Similarly, models 3 and 4 also control for daily changes in the intensity of the reporting activity by Anonymous and the suspending activity by Twitter, yet results remain substantively unaltered. Overall, these results confirm the effect of terrorist attacks on decreasing the number of followers on IS-related Twitter accounts, but we find that this effect is consistent across all accounts regardless of the value of the material capabilities of the state in which an account is located.

[Table 4 about here]

Overall, we see that the key prediction from the deterrence mechanism for that accounts located in stronger countries should be more affected by attacks is not supported by the results. The effect is similarly strong across all accounts regardless of the strength of the state in which the account is geographically located, which is contrary to the expectation based on the deterrence mechanism. This suggests that the disengagement mechanism rather than the deterrence mechanism is likely to be at work in our main analysis.

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20See more details in the "Data" section for a description on how the scores of the national material capabilities of the state are generated for these analyses.
6 Conclusion

Twitter has become a crucial communication and recruitment tool for the Islamic State. This paper offers an innovative approach to learning about the characteristics of IS by tracking the reports made by Anonymous on their Twitter accounts. The new data allows our study to explore an important question in political science in general and the terrorism literature in particular: what are the consequences of terrorist attacks? While providing a full answer to this issue is beyond the scope of this research, we have provided new empirical evidence on the impact of terrorist attacks on the number of supporters of terrorist organizations.

Our results shed light on the dynamics between those on the border between those insider and outside the organization. In particular, a strong empirical regularity has emerged from our analysis: terrorist attacks lead to a decrease in the size of IS’s Twitter audience in the aftermath of an attack that is both statistically and substantively significant. These results speak directly to the literature of the effectiveness of violence for terrorist organizations, by showing that the disengagement effect among likely supporters and sympathizers dominates both the mobilization and the attentional effects that terrorist attacks have on them. Hence, if a terrorist organization seeks to broaden its base of explicit supporters through violent activities, we show that this strategy is counter-productive because not only does their supporters not increase, but it significantly decreases.

Assuming rationality among terrorists, then the unaddressed puzzle is: why would terrorist organizations engage in violent activities if this causes a decrease in the number of people that will be reached or potentially recruited? We can speculate that the reduction in their Twitter audience is the price terrorists have to pay to accrue two benefits from attacks. First, attacks may not aim at broadening the base of supporters (external mobilization), but to increase the loyalty of those who were already members (internal mobilization); in other words, they might trade quantity for quality by radicalizing already-supporters at the expense of losing moderate supporters. In our research design, this is something that is unobserved. We do not see whether supporters move from passive to active, or from active to leader after terrorist attacks, because they are followers of the observed accounts both before and after an attack.
Finally, while attacks backfire by reducing the size of the Twitter audience, they may aim at infusing terror in the civil population. This may benefit the organization in terms of exerting influence over foreign governments, as suggested by a body of scholarship (e.g., Bueno de Mesquita, 2005; Bueno de Mesquita and Dickson, 2007). Possibly, infusing terror among the population may increase the likelihood of governments to either provide policy concessions (Thomas, 2014), or provoke an excessive response of government for the advantage of the organization (Bueno de Mesquita, 2005; Bueno de Mesquita and Dickson, 2007). Thus, the cost paid in a reduction in the number of people that can be reached through Twitter may be either worth taking or not the product of instrumental rationality. While this research focuses on a particular aspect of the relationship between the organization and society, we acknowledge that further research is required to fill the theoretical and empirical gaps that remain in this literature to fully understand the incentives of pursuing violent activities. In addition, this study has focused on the organization that is perhaps the most influential in today’s politics, Islamic State. However, future research should explore whether our findings can generalize to other types of terrorist organizations.

References


Mitts, Tamar. 2017. “From Isolation to Radicalization: Anti-Muslim Hostility and Support for ISIS in the West.”.


Table 1: Local Average Treatment Effects of Timing of the Attack on the Number of Twitter Followers

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Dependent Variable: Number of Followers</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td><strong>LATE: ( \bar{\tau} )</strong></td>
<td>-25.0*</td>
<td>-37.1*</td>
<td>-19.8**</td>
<td>-19.0**</td>
</tr>
<tr>
<td></td>
<td>(13.0)</td>
<td>(16.3)</td>
<td>(11.0)</td>
<td>(9.5)</td>
</tr>
<tr>
<td><strong>Bandwidth</strong></td>
<td>1 day</td>
<td>3 days</td>
<td>6 days</td>
<td>14 days</td>
</tr>
<tr>
<td></td>
<td>(half-IK)</td>
<td>(IK)</td>
<td>(double-IK)</td>
<td></td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>3,744</td>
<td>16,967</td>
<td>34,183</td>
<td>53,069</td>
</tr>
<tr>
<td><strong>Pre-treatment N</strong></td>
<td>2,858</td>
<td>8,542</td>
<td>17,077</td>
<td>17,077</td>
</tr>
<tr>
<td><strong>Post-treatment N</strong></td>
<td>2,825</td>
<td>8,425</td>
<td>17,106</td>
<td>35,992</td>
</tr>
</tbody>
</table>

**PANEL B: Terrorist Attack in Nice**

|                  | **Dependent Variable: Number of Followers** |                  |                  |                  |
|                  | (1)              | (2)              | (3)              | (4)              |
| **LATE: \( \bar{\tau} \)** | -58.6***          | -127.3***         | -40.1**          | -23.6**          |
|                  | (14.1)           | (22.4)           | (16.1)           | (11.4)           |
| **Bandwidth**    | 1 day            | 2 days           | 4 days           | 8 days           |
|                  | (half-IK)        | (IK)             | (double-IK)      |                  |
| **Observations** | 3,744            | 6,988            | 14,269           | 26,997           |
| **Pre-treatment N** | 2,003           | 6,988            | 14,269           | 26,997           |
| **Post-treatment N** | 1,741           | 3,714            | 7,711            | 15,554           |

**Note:** *p<0.1; **p<0.05; ***p<0.01. IK refers to Imbens and Kalyanaraman’s (2012) bandwidth.*
Table 2: The Impact of the Number of Victims in Attacks on the Number of Followers in IS-related Twitter Accounts

<table>
<thead>
<tr>
<th>PANEL A:</th>
<th>Dependent variable: Number of Followers (log scale)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Discount rate: 50%</td>
</tr>
<tr>
<td></td>
<td>(1.1)</td>
</tr>
<tr>
<td>Number of victims (US &amp; Europe) ('00)</td>
<td>−0.392***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
</tr>
<tr>
<td>Number of victims (outside US &amp; Europe) ('00)</td>
<td>−0.076***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
</tr>
<tr>
<td>Number of reports ('000)</td>
<td>0.064***</td>
</tr>
<tr>
<td>Number of suspensions ('00)</td>
<td>−0.090***</td>
</tr>
<tr>
<td>RE user-account</td>
<td>×</td>
</tr>
<tr>
<td>FE user-account</td>
<td>×</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PANEL B:</th>
<th>Discount rate: 75%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(2.1)</td>
</tr>
<tr>
<td>Number of victims (US &amp; Europe) ('00)</td>
<td>−0.394***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
</tr>
<tr>
<td>Number of victims (outside US &amp; Europe) ('00)</td>
<td>−0.073***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>Number of reports ('000)</td>
<td>0.066***</td>
</tr>
<tr>
<td>Number of suspensions ('00)</td>
<td>−0.090***</td>
</tr>
<tr>
<td>RE user-account</td>
<td>×</td>
</tr>
<tr>
<td>FE user-account</td>
<td>×</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>PANEL C:</th>
<th>Discount rate: 100%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(3.1)</td>
</tr>
<tr>
<td>Number of victims (US &amp; Europe) ('00)</td>
<td>−0.391***</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
</tr>
<tr>
<td>Number of victims (outside US &amp; Europe) ('00)</td>
<td>−0.071***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>Number of reports ('000)</td>
<td>0.044***</td>
</tr>
<tr>
<td>Number of suspensions ('00)</td>
<td>−0.004***</td>
</tr>
<tr>
<td>RE user-account</td>
<td>×</td>
</tr>
<tr>
<td>FE user-account</td>
<td>×</td>
</tr>
</tbody>
</table>

N total 239,434 218,727 239,434 218,763
N accounts 10,554 8,320 10,554 8,320
N days 127 127 127 127

Note: *p<0.1; **p<0.05; ***p<0.01. Constants omitted from the output. Columns 1 and 3: OLS regressions with standard errors clustered by account. Columns 2 and 4: Fixed-effects models at the account-level with standard errors clustered by account. The number of observations in the fixed effects models is lower because accounts with one observation are excluded from the dataset for identification purposes. In all models, we have excluded extreme observations in the dependent variable—the top 1% percentile, yet results are unaltered if we include them.
Table 3: Predicted Percentage Change in the Number of Followers After Some Important Terrorist Events within our Sample Period

<table>
<thead>
<tr>
<th>Terrorist Attack</th>
<th>Date of the Attack</th>
<th>Location</th>
<th>Number of deaths</th>
<th>Predicted Cumulative % Change in the Number of Followers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brussels bombings</td>
<td>22 March 2016</td>
<td>Brussels, Belgium</td>
<td>36</td>
<td>-3.00%</td>
</tr>
<tr>
<td>Yemen bombings</td>
<td>23 May 2016</td>
<td>Aden, Yemen</td>
<td>45</td>
<td>-0.8%</td>
</tr>
<tr>
<td>Atatürk airport attack</td>
<td>28 June 2016</td>
<td>Istanbul, Turkey</td>
<td>44</td>
<td>-3.6%</td>
</tr>
<tr>
<td>Karrada bombings</td>
<td>3 July 2016</td>
<td>Baghdad, Iraq</td>
<td>341</td>
<td>-5.6%</td>
</tr>
<tr>
<td>Nice attack</td>
<td>14 July 2016</td>
<td>Nice, France</td>
<td>86</td>
<td>-7.1%</td>
</tr>
</tbody>
</table>

*Note:* Simulated values are based on the fixed-effects models from column 3 in Table 3.

Table 4: The Impact of the Number of Victims in Attacks Linked to IS on their Number of Followers in Twitter by Countries’ National Material Capabilities

<table>
<thead>
<tr>
<th></th>
<th>Number of Followers (log scale)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>NMC Score</td>
<td>−0.076***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td>Number of victims (US &amp; Europe) (00’)**</td>
<td>−0.382***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
</tr>
<tr>
<td>Number of victims (outside US &amp; Europe) (00’)**</td>
<td>−0.075***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
</tr>
<tr>
<td>Number of victims (US &amp; Europe) (00’) × NMC Score</td>
<td>−0.016</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
</tr>
<tr>
<td>Number of victims (outside US &amp; Europe) (00’) × NMC Score</td>
<td>−0.002</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
</tr>
<tr>
<td>Number of reports (’000)</td>
<td>0.079***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>Number of suspensions (’00)</td>
<td>−0.078***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
</tbody>
</table>

*Note:* *p < 0.1; **p < 0.05; ***p < 0.01. Constants omitted from the output. Column 1 and 3: OLS regressions. Columns 2 and 4: Fixed-effects model at the account-level with standard errors clustered by account with the number of victims interacted with a time-invariant characteristic of the accounts, the predicted score of the National Material Capabilities (NMC) in the account’s country of residence. Models in columns 2 and 4 are also referred to as a hybrid model because it provides variation in a time-invariant variable (NMC of the account) because of its interaction with a time-variant variable (number of victims), while maintaining any other characteristic of the account constant. The coefficient of the NMC score has to be excluded in the hybrid models because the constitutive term is time-invariant, so it cannot be separately estimated with the fixed effects. Just as for the main analysis, the number of observations in the fixed effects models is lower because accounts with one observation are excluded from the dataset for identification purposes. In all models, we have excluded extreme observations in the dependent variable—the top 1% percentile, yet results are unaltered if we include them.
Figure 1: Cumulative Lagged Measure of Deaths from Terrorist Attacks by IS (03/16/2016—07/20/2016)
Figure 2: Interrupted Time Series of Followers by Two Major Attacks

(a) IS Attack in Brussels, Belgium (March 22, 2016)  
(b) IS Attack in Nice, France (July 14, 2016)

Figure 3: Predicted Values of the Number of Followers Depending on the Number of Cumulative Deaths and the Location of IS’s Terrorist Attacks
Online Appendix to:

“Global Terrorism and (De-)Mobilization: Do IS’s Deadly Attacks Disengage, Deter, or Mobilize Supporters?”

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A  Formal modelling of the response to an IS attack

The purpose of this section is to analytically identify the sources of the change in the number of the followers of the reported accounts as a response to the IS attacks. As already proposed, the observed number of the followers consists of the group of leaders, as well as actively and passively involved people who are not in a leadership position; furthermore, some followers are just “observers”: terrorism fighters, analysts or journalists. Hence, we model the mechanism of transition between those categories and non-followers. In this section, we provide a formal justification for our main hypothesis and show that finding a negative effect of the IS attack on the number of Twitter followers indicates that the de-mobilization effect of the attacks is stronger than the mobilization effect across ground boundaries.

Importantly, the following model contains five categories while empirically we can discriminate only between followers and non-followers. We use here five categories rather than three because we unpack insiders of the organization in three categories of intensity: leaders, active, and passive members. Having a richer classification in the formal model than in the data is crucial as it enables to underline three key points. First of all, this model proposes a simple way to look into the general dynamics of the online extremist mobilization on Twitter. Second, as a result of the first point and crucially for our main argument, it allows showing explicitly that the existence of the hidden within-group mobilization dynamics does not contradict our hypotheses about the mobilization dynamics given our data. Third, the model explicitly links the broader formal setting to our causal empirical claims, providing additional evidence for them.

A.1 Individual transition model

Based on the classification in the previous section, here we describe the individual likelihoods of the transition between the categories. The stochastic matrix (Table A.1) formalizes our substantive assumptions about the types of the followers and their likely responses to a terrorist attack by IS. We design the movements across the categories as a Markov process with no memory - only the current state affects the possible dynamics. Clearly, from the substantive perspective, the history influences
the current position as well. However, since all that information is embedded in the present state the lagged variables are omitted. The model has five individual states, two of which are fixed-points: “leader” and “observer.” Meanwhile, three other states enable movements up or down one category regarding the individual mobilization.

<table>
<thead>
<tr>
<th>Table A.1: Individual category transition stochastic model</th>
</tr>
</thead>
<tbody>
<tr>
<td>leader group</td>
</tr>
<tr>
<td>leader group</td>
</tr>
<tr>
<td>active</td>
</tr>
<tr>
<td>passive</td>
</tr>
<tr>
<td>non-followers</td>
</tr>
<tr>
<td>observers</td>
</tr>
</tbody>
</table>

Each row shows the non-zero probabilities of the member of a particular group to transition to another category or to stay in the same category: $\alpha_0 + \alpha_1 + \alpha_2 = 1$, $\beta_0 + \beta_1 + \beta_2 = 1$, and $\gamma_0 + \gamma_1 + \gamma_2 = 1$. First, we assume that the current IS’s leaders do not respond in any way to the attack. That is why the only non-zero value on the first row is on the diagonal. Contrary to them, the active supporters might become more or less mobilized as a response to the attack, or they might keep the same level of interest. Most importantly, we assume that they will be still among the detected followers even if their support becomes milder. The categories providing the variation in the observed numbers of the followers are passive supporters and former non-followers. Talking of the passive supporters, some of them might radicalize. Meanwhile, some may dislike what they see or become afraid of being tracked as connected to IS and stop following IS. The observers, who are most likely IS enemy fighters or journalists following IS, will not change their behavior as a response to the attack. Finally, some of the non-followers might become passive supporters as the terrorist attack makes IS more visible; this would imply a broadening of the base of supporters of the organization—what we call the effect of mobilizing outsiders.

A.2 Group comparative statistics

Let’s denote: $x = (x_1, x_2, x_3, x_4, x_5) = (\text{leader group, active, passive, non-followers, observers})$.

Our data enables us to observe the total number of the followers of the reported accounts. This is
the exact upper bound of the actual total number of the people in categories 1-3 and 5, since some reported Twitter accounts may have common users following them. We assume that the correlation between the observed upper bound and the total number of the distinct followers is approximately the same before and after the attack. Hence, if we observe the decrease in the exact upper bound after the attack, it indicates a decline in the total number in categories 1-3 and 5.

To sum up, the total observed number of the followers as:

\[ x^* = x_1 + x_2 + x_3 + x_5 \]

where \( x_i \) denotes the number of the people in group \( i \) (\( x_4 \) are the non-followers before a terrorist attack). We need to estimate \( E(x^*) \) the expected number of the observed followers after the attack based on Table A.1. Given that every follower is independent of one another, the estimates for the categories after the attack are:

\[
E(x^*) = A' x' = \begin{pmatrix}
    x_1 + \alpha_0 x_2 \\
    \alpha_1 x_2 + \beta_0 x_3 \\
    \alpha_2 x_2 + \beta_1 x_3 + \gamma_0 x_4 \\
    \beta_2 x_3 + \gamma_1 x_4 \\
    \gamma_2 x_4 + x_5
\end{pmatrix}
\]

Summing up, what we observe after an attack:

\[
x^*_1 + x^*_2 + x^*_3 + x^*_5 = x_1 + x_2 + (\beta_0 + \beta_1)x_3 + (\gamma_0 + \gamma_2)x_4 + x_5
\]

Hence, the observed change is:

\[
\sum_{i=1,2,3,5} x^*_i - \sum_{i=1,2,3,5} x = \delta = -\beta_2 x_3 + (\gamma_0 + \gamma_2)x_4
\]  

(1)

where \( \beta_2 x_3 \) is the de-mobilization effect, \( \gamma_0 x_4 \) is the effect of mobilizing outsiders.

Hence:

\[
\delta < 0 \implies \{ \gamma_2 x_4 > 0 \} \implies \beta_2 x_3 > \gamma_0 x_4
\]  

(2)

Importantly, because of \( \gamma_2 x_4 \neq 0 \) if \( \delta > 0 \) we are not able to evaluate the relation between the
external de-mobilization effect, $\beta_2 x_3$, and the effect of mobilizing outsiders, $\gamma_0 x_4$.

Three possible empirical outcomes conclude this formal section. If we observe an *increase* in the total number of followers of the reported accounts, it implies that the combination of the mobilization and the attention effect dominates the de-mobilization effect ($\gamma_0 x_4 + \gamma_2 x_4 > \beta_2 x_3$). If the number of followers is not altered, then it must be the case that the de-mobilization effect cancels the other two effects ($\gamma_0 x_4 + \gamma_2 x_4 = \beta_2 x_3$) and we still could claim that $\beta_2 x_3 > \gamma_0 x_4$. Finally, if we observe a *decrease* in $\delta$, the de-mobilization effect of the attacks dominates their mobilization effect ($\gamma_0 x_0 < \beta_2 x_3$).
## B  Terrorist Data: List of Attacks and Number of Victims

### Table B.1: List of ISIS’s Attacks in the Analysis

<table>
<thead>
<tr>
<th>Terrorist Attack</th>
<th>Date of the Attack</th>
<th>Location</th>
<th>Number of Deaths</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Istanbul Explosion</td>
<td>19 March, 2016</td>
<td>Istanbul, Turkey</td>
<td>4</td>
<td>Dearden (2016); Tattersall and Yackley (2016)</td>
</tr>
<tr>
<td>Yemen Bombings I</td>
<td>25 March, 2016</td>
<td>Aden, Yemen</td>
<td>26</td>
<td>“Yemen Bombings” (2016)</td>
</tr>
<tr>
<td>Iraq Stadium</td>
<td>25 March, 2016</td>
<td>Al-Asriya, Iraq</td>
<td>33</td>
<td>“Iraq buries young” (2016); “Iraq Violence” (2016)</td>
</tr>
<tr>
<td>Attack on LGBT activists</td>
<td>25 April, 2016</td>
<td>Dhaka, Bangladesh</td>
<td>2</td>
<td>“Editor Hacked” (2016)</td>
</tr>
<tr>
<td>Baghdad Bombing I</td>
<td>30 April, 2016</td>
<td>Baghdad, Iraq</td>
<td>38</td>
<td>Adel (2016)</td>
</tr>
<tr>
<td>Samawa Twin Explosion</td>
<td>1 May, 2016</td>
<td>Samawa, Iraq</td>
<td>33</td>
<td>“Rare IS Bombings” (2016)</td>
</tr>
<tr>
<td>Baghdad Bombings II</td>
<td>11 May, 2016</td>
<td>Baghdad, Iraq</td>
<td>110</td>
<td>“IS Kills Dozens” (2016)</td>
</tr>
<tr>
<td>Real Madrid Massacre I</td>
<td>13 May, 2016</td>
<td>Balad, Iraq</td>
<td>16</td>
<td>Stephen (2016)</td>
</tr>
<tr>
<td>Real Madrid Massacre II</td>
<td>29 May, 2016</td>
<td>Balad, Iraq</td>
<td>12</td>
<td>Couzens (2016)</td>
</tr>
<tr>
<td>Yemen Bombings II</td>
<td>23 May, 2016</td>
<td>Aden, Yemen</td>
<td>45</td>
<td>“ISIL Blamed” (2016)</td>
</tr>
<tr>
<td>Aktobe Shootings</td>
<td>5/8 June, 2016</td>
<td>Aktobe, Kazakhstan</td>
<td>7</td>
<td>“Police Arrest” (2016); Dubnov (2016)</td>
</tr>
<tr>
<td>Magnanville Stabbing</td>
<td>13 June, 2016</td>
<td>Magnanville, France</td>
<td>2</td>
<td>“French Jihadist” (2016)</td>
</tr>
<tr>
<td>Qaa Bombings</td>
<td>27 June, 2016</td>
<td>Qaa, Lebanon</td>
<td>5</td>
<td>“Lebanon” (2016)</td>
</tr>
<tr>
<td>Ataturk Airport</td>
<td>28 June, 2016</td>
<td>Istanbul, Turkey</td>
<td>44</td>
<td>“Airport Attack” (2016)</td>
</tr>
<tr>
<td>Dhaka Attack</td>
<td>1 July, 2016</td>
<td>Dhaka, Bangladesh</td>
<td>21</td>
<td>Hanna et al. (2016)</td>
</tr>
<tr>
<td>Karrada Bombings</td>
<td>3 July, 2016</td>
<td>Baghdad, Iraq</td>
<td>341</td>
<td>Adel (2016)</td>
</tr>
<tr>
<td>Saudi Arabia Bombings</td>
<td>4 July, 2016</td>
<td>Saudi Arabia</td>
<td>4</td>
<td>Robertson et al. (2016)</td>
</tr>
</tbody>
</table>

**Note on inclusion/exclusion criterion:** A borderline case is the attack on the *Purse club* in Orland, on June 14, 2016. Though some initial information linked it to Islamic State, Barack Obama addressed the nation shortly after the attack by stating that the Orland attack had been an act of "homegrown terrorism" carried out by legally purchased firearms ("Orlando Shooting" (2016)). This contrasts to François Hollande statement immediately after the truck attack on Nice, who strongly linked it to ISIS by stating that “all of France is being menaced by Islamic fundamentalist terrorism”. Because our treatment effect should be evaluated in the short-term with the available information at that time, we choose to code the Nice attack as an ISIS’s attack, and the Orlando attack as a "home-grown" hate crime (Mestre, Revault d’Allonnes and Bissuel, 2016).

**Note on measurement error:** Figures on the number of deaths are approximate because they may vary depending on the news source.
C  Google Trends and the Cumulative Lagged Measure of Deaths

Figure C.1 shows the cumulative death parameter around the Brussels bombings on March 22, 2016, with r=0.5, as having values of 0, 36, 24, 16, 10.67, and so on, for the days between 21th to 25th March, respectively. This discount pattern parallels the changes in the keywords “Brussels bombing” reported by Google Trends. On the date of the occurrence, Google trends reports a value of 100 (its standardized base value), a decrease to 7 one week later, and a further decrease to 0 two weeks later. Similarly, if we applied a discount factor of, for example, 50% to an event with 100 deaths—as the base in Google trends for comparison—then the trend would be 100 in the same day, 5.85 a week later, and 0.34 two weeks later. The correlation of Google attention to the event and our cumulative value is above 0.90 within a one-month window around the event. Other attacks in the sample do not differ in the evolution of their attention over time, but some of them had obviously less overall attention. It is worth noting that choosing a greater discount parameter does not alter any of the results presented in the paper.

Figure C.1: Google Trends and the Cumulative Lagged Measure of Deaths: Brussels Bombings (keywords “Brussels Bombing”
D Predicting the National Material Capabilities (NMC)

In the last section of our paper, we look at how National Material Capabilities (NMC) of the country in which the account is located moderates the effect of the terrorist attacks on the number of followers of likely IS-related accounts. The country of a Twitter account defines its relative NMC. However, not all accounts have information enabling to determine their geographic origin. Therefore, we implement an imputation process to generate NMCs for those accounts from which we do not have sufficient information to determine their geographic location.

D.1 Inferring the country of origin

The profile information of each Twitter account has the feature location. This field is self-reported and voluntary. Therefore, many users leave this field empty (9580 of 13,300 or 72% of our sample). However, 1615 observations (43% of the non-empty or 12% of our sample) have sufficient information to infer their country. Table D.1 shows the shares of the countries that we can observe. They constitute the observations in our training dataset.

D.2 Matching accounts to the NMC: Clusterization of the countries

The distribution in our training set is unbalanced relative to the countries: for some countries we do not have enough information to reliably train a machine learning model to predict the country of account’s origin. Therefore, we cannot predict the specific country of all the accounts that do not report their country of origin. Yet, we can reliably predict the account’s characteristic of interest, the NMC of the account’s country. This is a continuous attribute with much less variation. As Figure D.1 shows, the distribution is not uniform and proposes to take its clustered structure into account. We use the K-means algorithm to assign all countries based on their NMC to 5 clusters with the incremental labels.
Table D.1: Shares of the Twitter accounts by country (training dataset)

<table>
<thead>
<tr>
<th>Country</th>
<th>Share</th>
<th>Country</th>
<th>Share</th>
<th>Country</th>
<th>Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Syria</td>
<td>11.19%</td>
<td>Russia</td>
<td>0.98%</td>
<td>Maldives</td>
<td>0.43%</td>
</tr>
<tr>
<td>Iraq</td>
<td>10.46%</td>
<td>Spain</td>
<td>0.98%</td>
<td>Mexico</td>
<td>0.43%</td>
</tr>
<tr>
<td>United states</td>
<td>6.73%</td>
<td>Lebanon</td>
<td>0.92%</td>
<td>Philippines</td>
<td>0.43%</td>
</tr>
<tr>
<td>United kingdom</td>
<td>5.69%</td>
<td>Algeria</td>
<td>0.86%</td>
<td>Brazil</td>
<td>0.37%</td>
</tr>
<tr>
<td>Indonesia</td>
<td>5.38%</td>
<td>Malaysia</td>
<td>0.86%</td>
<td>China</td>
<td>0.37%</td>
</tr>
<tr>
<td>Turkey</td>
<td>5.38%</td>
<td>Somalia</td>
<td>0.86%</td>
<td>Ukraine</td>
<td>0.37%</td>
</tr>
<tr>
<td>France</td>
<td>4.71%</td>
<td>Japan</td>
<td>0.80%</td>
<td>Nigeria</td>
<td>0.31%</td>
</tr>
<tr>
<td>Saudi arabia</td>
<td>4.46%</td>
<td>Kuwait</td>
<td>0.80%</td>
<td>Romania</td>
<td>0.31%</td>
</tr>
<tr>
<td>Egypt</td>
<td>3.91%</td>
<td>Morocco</td>
<td>0.80%</td>
<td>Singapore</td>
<td>0.31%</td>
</tr>
<tr>
<td>Israel</td>
<td>3.12%</td>
<td>Australia</td>
<td>0.73%</td>
<td>Argentina</td>
<td>0.24%</td>
</tr>
<tr>
<td>Germany</td>
<td>2.08%</td>
<td>Italy</td>
<td>0.73%</td>
<td>Bosnia and Herzegovina</td>
<td>0.24%</td>
</tr>
<tr>
<td>Libya</td>
<td>2.02%</td>
<td>Sweden</td>
<td>0.67%</td>
<td>New Zealand</td>
<td>0.24%</td>
</tr>
<tr>
<td>Afghanistan</td>
<td>1.96%</td>
<td>United Arab Emirates</td>
<td>0.67%</td>
<td>Norway</td>
<td>0.24%</td>
</tr>
<tr>
<td>India</td>
<td>1.83%</td>
<td>Belgium</td>
<td>0.55%</td>
<td>Austria</td>
<td>0.18%</td>
</tr>
<tr>
<td>Canada</td>
<td>1.59%</td>
<td>Switzerland</td>
<td>0.55%</td>
<td>Bahrain</td>
<td>0.18%</td>
</tr>
<tr>
<td>Pakistan</td>
<td>1.28%</td>
<td>Qatar</td>
<td>0.49%</td>
<td>Denmark</td>
<td>0.18%</td>
</tr>
<tr>
<td>Yemen</td>
<td>1.28%</td>
<td>Bangladesh</td>
<td>0.43%</td>
<td>Ethiopia</td>
<td>0.18%</td>
</tr>
<tr>
<td>Netherlands</td>
<td>1.16%</td>
<td>Brasil</td>
<td>0.43%</td>
<td>Iran</td>
<td>0.18%</td>
</tr>
<tr>
<td>Tunisia</td>
<td>1.04%</td>
<td>Finland</td>
<td>0.43%</td>
<td>Oman</td>
<td>0.18%</td>
</tr>
<tr>
<td>Jordan</td>
<td>0.98%</td>
<td>Ireland</td>
<td>0.43%</td>
<td>Other</td>
<td>4.40%</td>
</tr>
</tbody>
</table>
Figure D.1: National Material Capacities: Ordered accounts
D.3 Training a machine learning model

The classification algorithms are well-developed in machine learning and, importantly for us, have very clear evaluation measures. In particular, we can explicitly see how many values in the data-set are predicted correctly. That is why we are making use of the clustered structure of NMCs. We train the ordinal regression model using the Two-Class Boosted Decision Tree (Elith, Leathwick and Hastie, 2008) based on the features that we have for all accounts in our dataset: language, time-zone, number of friends, and number of favorites, and number of statuses\(^{21}\). Figure D.2 shows the results from 10-fold cross-validation for the trained model. In addition, we can see that the prediction model has a very good fit. Hence, we apply the trained model to obtain NMC results for the rest of the sample. Overall, this procedure generates NMC scores for all accounts in our sample. At one extreme, those accounts located in a weak country have a NMC score of 0. At the other extreme, those accounts located in countries with strong material capabilities have a score of 4.

Table D.2: Cross-validation: Ordinal Regression via the Two-Class Boosted Decision Tree

<table>
<thead>
<tr>
<th>Fold Number</th>
<th>Observations</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>162</td>
<td>0.17</td>
</tr>
<tr>
<td>1</td>
<td>161</td>
<td>0.16</td>
</tr>
<tr>
<td>2</td>
<td>161</td>
<td>0.14</td>
</tr>
<tr>
<td>3</td>
<td>162</td>
<td>0.12</td>
</tr>
<tr>
<td>4</td>
<td>162</td>
<td>0.13</td>
</tr>
<tr>
<td>5</td>
<td>161</td>
<td>0.15</td>
</tr>
<tr>
<td>6</td>
<td>162</td>
<td>0.14</td>
</tr>
<tr>
<td>7</td>
<td>161</td>
<td>0.14</td>
</tr>
<tr>
<td>8</td>
<td>161</td>
<td>0.12</td>
</tr>
<tr>
<td>9</td>
<td>162</td>
<td>0.14</td>
</tr>
<tr>
<td>Mean</td>
<td>1615</td>
<td>0.14</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1615</td>
<td>0.02</td>
</tr>
</tbody>
</table>

\(^{21}\)We do not include the number of followers in the features used to train the model, since we use it as a dependent variable further in the analysis.
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