

What makes a jihadist text popular?

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Abstract

Jihadist militants often spread their ideas to potential followers through online communications. We analyze 50 million page views of a prominent jihadist web library to identify features of these communications that drive their popularity. We find that author identity is a more accurate predictor of a documents popularity than topic, format, or position within the repository, suggesting that jihadists base their reading decisions on authority. We also find that key events in the development of the Islamic State coincide with temporary increases in the popularity of texts by Sayyid Qutb, a founding father of the jihadist movement. Surprisingly, we find no evidence that counterterrorism operations lead to a sustained martyrdom effect, as the increase in popularity of writings by targeted authors is only temporary. Consequently, fears that counterterrorism efforts will inadvertently repopularize jihadists ideas are overblown, but counterterrorism efforts do not appear to make jihadists ideas less popular either.

1 Introduction

On May 1, 2011, Usama Bin Laden was a struggling author. He was still the most famous living transnational jihadist and his ideas had shaped the jihadist movement but now his relevance was in question. Forced into hiding by a global manhunt, Bin Laden had failed to produce major new works for years. His statements and ideas leaked out in a trickle, with questionable influence on other jihadists. Twenty-four hours later, Bin Ladens face was on the front page of most major newspapers and his writings were being accessed at a furious rate online. True, he was dead – killed by a team of Navy SEALs in his secret Abbottabad compound – but his writings were again popular, at least momentarily. And what every author wants, violent jihadists included, is for their ideas to be read.

Although it is impossible to fully quantify the influence of Bin Ladens ideas, their global effects are profound. In other domains, scholars debate whether

32 ideas matter for shaping political outcomes [1, 2, 3, 4], but the ideas preached by
33 Bin Laden and his ilk have been so catastrophically effective that their influence
34 is not generally in doubt. Rather, the pressing issue is how these ideas can be
35 snuffed out, or at least quarantined to the fringes of Islamist discourse.

36 The content and evolution of jihadist ideology is well understood [5] and
37 surveys give some insights about the cross-national variation in popular support
38 for violent jihad [6]. New research shows that the availability of international
39 funding shifts the content of jihadist messages [7]. However, less is known about
40 why some jihadist ideas gain more popularity than others. Understanding what
41 drives the popularity of jihadist online writing is important for any effective
42 policy to limit the influence of jihadist ideas. The fact that counterterrorism
43 resources are finite elicits the following fundamental question: When any new
44 piece of writing appears, is it worth the effort to try to suppress it?

45 Counterterrorism strategies may also have unintended consequences. Killing
46 and capturing jihadist leaders like Usama Bin Laden has been a key strat-
47 egy of US counterterror efforts. Yet, some observers have expressed concern
48 that counterterrorism strengthens the appeal of violent jihadism by elevating
49 its most vociferous proponents to the status of martyrs [8, 9, 10]. Others claim
50 that these fears are overblown, and that the killings of Bin Laden and other
51 jihadist thinkers over the past decade have been a serious blow to Al-Qaeda,
52 with no blowback effect [11]. Prior research suggests that drone strikes against
53 Al Qaeda did not affect their subsequent propaganda production [12], but this
54 research does not have data to test whether existing propaganda became more
55 or less popular. Given these contradictory views and lack of data, researchers
56 and counterterrorism experts are often in the dark about how to best counter
57 jihadists' violent ideas and actions.

58 This paper quantitatively investigates what drives the viewership of jihadist
59 writings posted online. We posit two logics of viewership. According to a news-
60 worthiness logic of viewership, a document is likely to become popular because
61 of its topical content, timeliness, and sensationalism. This is the logic of popu-
62 larity that many observers seem to have in mind when discussing the threat of
63 jihadist media, see for example [13]. In contrast, an authority logic of viewership
64 suggests that a document is likely to become popular because of the eminence
65 of its author, rather than its content. We believe that individuals who click
66 on jihadist materials because of an authority logic are much more concerning
67 than individuals following a newsworthiness logic. Someone who clicks on a
68 document because it is newsworthy is merely trying to stay informed about the
69 world. Someone who clicks because of authority is potentially interested in tak-
70 ing the ideas to heart, and in the context of jihadism, that may encourage them
71 to carry out political violence. The average person who accesses a jihadist text
72 because its author is mentioned in the news is not likely to become violent. By
73 contrast, a reader who is intentionally reading jihadists for their ideas might be.

74 We use page-view data from a large jihadist web-library to show that au-
75 thority, rather than content, is the most important factor in making a jihadist
76 text popular. We also examine whether killing jihadist thinkers inadvertently
77 increases the popularity of their ideas. We find that it does, but only tem-

78 porarily. We compare both of these results to a very different domain where
79 authority matters: academic scholarship in physics, engineering, and related
80 fields. We find a remarkable correspondence between patterns of viewership on
81 the jihadist web library and on a large online repository of academic papers.
82 This correspondence suggests that most of the viewership of the jihadist web
83 library follows an authority logic, and that jihadist authority is similar in some
84 ways to academic authority. The exception is that spikes of interest following
85 the death of jihadist writers appears to follow a newsworthiness logic.

86 2 Popularity in *The Pulpit of Monotheism and* 87 *Jihad*

88 Contradictory views on what makes jihadist texts popular exist in part due to
89 a dearth of systematic, data-centric approaches to this question. To shed light
90 on this issue, we analyze the popularity of documents on a prominent jihadist
91 web library, *The Pulpit of Monotheism and Jihad*, which was the premier source
92 on the open web for Arabic-language jihadist material until its removal in 2015.
93 Jihadists regard the website as important – Bin Laden asked about it specifically
94 in documents recovered from his hideout in Pakistan – and scholars have called
95 it Al Qaeda’s premier electronic library [14].

96 The website reported page-view counts for each document in real time, pro-
97 viding a fine-grained measure of the popularity of jihadist texts with their in-
98 tended audience. Alexa web statistics service reports visitors to *The Pulpit of*
99 *Monotheism and Jihad* from throughout the Arab world, especially Egypt, Al-
100 geria, Tunisia, and Morocco¹. We are the first to analyze this web traffic, though
101 other scholars have investigated this website qualitatively [14, 15]. These page
102 views are the best available measure of jihadists’ popularity, and we find that
103 they correlate with the prominence of jihadist authors as measured by citations
104 in other canonical jihadist collections (see Supplementary Materials for more
105 details).

106 We used automated web crawlers to collect the cumulative daily page views
107 reported by the website from February 11th 2011 to December 6th 2014, adding
108 to more than 50 million page views. Consequently, associated with each doc-
109 ument we have a corresponding time series of cumulative views at the daily
110 scale; see Fig. S1. These time series contain gaps due to either website mal-
111 functions or faults in the data collection software. In Fig. S2 we report the
112 total number of documents for which we have a cumulative view count in each
113 day. The overall increasing trend is due to the addition of new documents to
114 the repository throughout the period of study. By the end of 2014, the web-
115 site contained 6,101 documents, ranging from long theological treatises to short
116 fatwas, by 865 authors. Two cleaning procedures were applied to the data of
117 cumulative views: i) imputation of missing data, and ii) outlier detection; see

¹<https://www.alexa.com/siteinfo/tawhed.ws>, accessed 3/17/2014 and archived by the authors because the website is now offline.

118 Materials and Methods for more details. Fig. 1A shows the cleaned cumulative
119 views. The distribution of average page views is skewed, as are the distributions
120 of documents per author and views per author; see Fig. 1B-D.

121 In addition to the cumulative views for each document, we also collect docu-
122 ment metadata: attributes such as author, length, or location within the repos-
123 itory (see the Supplementary Material for a complete list). At the beginning
124 of our data acquisition procedure, i.e. February 11th 2011, the repository con-
125 tained 5,236 documents by 776 different authors. Throughout the 1395 days in
126 which data was collected, 879 new documents were added to the repository and
127 14 were removed. Some additions have a close relation to concurrent political
128 events. For example, one of the four documents added on January 24th 2014
129 was the letter An Urgent Call to Our People in Syria by Ayman al-Zawahiri.
130 This occurred exactly the day after this letter was made public by Al-Qaeda’s
131 leader. This is also a testament of how active the repository was during the
132 data collection period.

133 New documents added to the repository are often advertised on the web-
134 site’s homepage, but only for a matter of days or weeks (Fig. S3). This website
135 architecture causes rapid accumulation of page views immediately after docu-
136 ments are posted, but view counts stabilize when homepage advertising stops;
137 see Supplementary Materials for more details. To show the difference between
138 these uptake and steady state phases, Fig. 1E depicts the normalized cumula-
139 tive views for the first 60 days of each document. More precisely, we plot the
140 cumulative views for the first 60 days of each document as a fraction of the
141 total views accumulated by that document in the first 60 days. If the daily
142 views were constant, the normalized cumulative views would align diagonally
143 (coinciding with the dashed straight line). Instead, all new documents are above
144 the diagonal and show decreasing page-view rates as time passes. In contrast,
145 Fig. 1F shows the same documents but 121 to 180 days after posting, with daily
146 page-view rates that are generally stable. Figs. 1E-F point towards the fact that
147 each document undergoes a boost of interest when added and then switches to
148 a more stable and mature steady-state rate of daily views. We use this rate of
149 views as a measure of the intrinsic popularity of each document.

150 **3 Results and Discussion**

151 **3.1 Popularity prediction**

152 What makes some documents more popular than others among jihadists? Notice
153 that our goal is not to make claims about the popularity of general online texts
154 but rather to pinpoint the popularity drivers within this specific target group.
155 To begin answering this question, we build a predictive model of the number
156 of daily page views that a newly posted document is likely to obtain. We
157 study whether features of the text and their authors can explain documents’
158 popularity. We consider four classes of features: source (such as author or
159 magazine), topic (such as topic models see Materials and Methods or words in

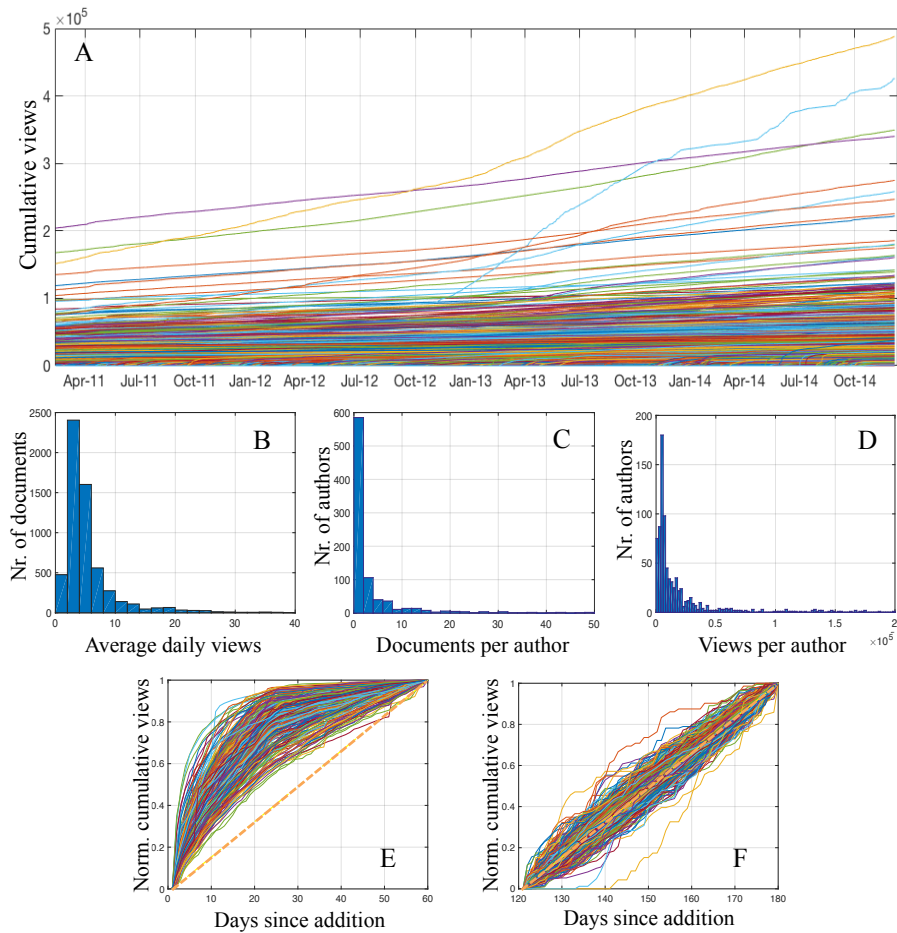


Figure 1: Viewership patterns of jihadist texts. (A) Cleaned cumulative views for every document in the database over the period of study. (B-D) Histograms describing (B) the average daily views per document [mean = 5.9, median = 4.1], (C) the documents per author [mean = 7.1, median = 1], and (D) the total views per author [mean = 57k, median = 8k]. The tails of all histograms have been truncated to facilitate visualization. (E-F) Normalized cumulative views for new documents in (E) the first 60 days and (F) from day 121 to 180.

160 the title), form (such as the use of poetry or easy-to-read language), and website
161 structure (such as the position of the document within a subpage). All the
162 features considered can be found in Table 1. For simplicity and interpretability,
163 we constrain ourselves to a sparse linear regression model [16] where we predict
164 the popularity of each document as a linear function of a sparse subset of the
165 features; see Materials and Methods. Although alternative nonlinear prediction
166 models might offer modest improvements in prediction accuracy, our goal is to
167 obtain a model that is both sufficiently accurate and interpretable.

168 To obtain the corpus of documents used for training and testing our regres-
169 sion model, we filter the documents via two procedures that we call rare-source
170 filtering and impulsive denoising (Materials and Methods). Rare sources are au-
171 thors (or magazines) with so few documents that our out-of-sample prediction
172 is not reliable, so we exclude documents from these sources. Our impulsive de-
173 noising procedure discards documents that are particularly popular for idiosyn-
174 cratic reasons, such as documents that played a unique role in the development
175 of jihadist thought. These are documents that would be better explained in our
176 model by a document-fixed effect, rather than by the predictors (Fig. S4). Each
177 of these two cleaning procedures is controlled by an adjustable parameter and
178 all the results stated here are robust to changes in these parameters (Fig. S5).

179 In Fig. 2A we plot the predicted popularity of all the documents consid-
180 ered (out-of-sample prediction based on 10-fold cross validation; cf. Fig. S4)
181 against their true daily views. Notice the accumulation along the diagonal,
182 demonstrating a good fit of the model. Indeed, the relative error obtained is
183 $\|\hat{\mathbf{y}} - \mathbf{y}\|_1 / \|\mathbf{y}\|_1 = 0.157$, where \mathbf{y} is a vector containing the real daily views
184 for all documents and $\hat{\mathbf{y}}$ contains the predicted daily views. This means that,
185 on average, we misestimate the steady-state daily view rate of a document by
186 15.7%. Having established the predictive capabilities when all features are con-
187 sidered, we repeat the prediction only based on one class of features at a time.
188 As expected, the performance markedly decreases, but the source features (au-
189 thorship) retain the best predictive power with a relative error of 22.7%. The
190 explanatory power of the topic is comparable to that of the website features,
191 achieving respective errors of 27.0% and 26.0%. Finally, features related to for-
192 mat (text length, lines of poetry, use of easy-to-read Arabic words) have very
193 little influence on the popularity enjoyed by jihadist texts with a prediction er-
194 ror of 40.9%; see Fig. 2B. Moreover, the relevance of the source is ratified when
195 checking the regression coefficient associated with the explicit author feature;
196 see Table 1. First, this coefficient is non-zero in the optimal sparse model. Most
197 importantly, this coefficient is positive indicating that stating the author of a
198 document explicitly is associated with 2.4 more daily views.

199 These results suggest that authorship – more than topic – drives the interest
200 of jihadist readers. In this context, one could argue that counterterrorism op-
201 erations targeting specific authors could decelerate the spread of violent ideas.
202 However, these operations drive publicity to the targeted authors potentially
203 increasing general interest in their ideas. We study this effect next.

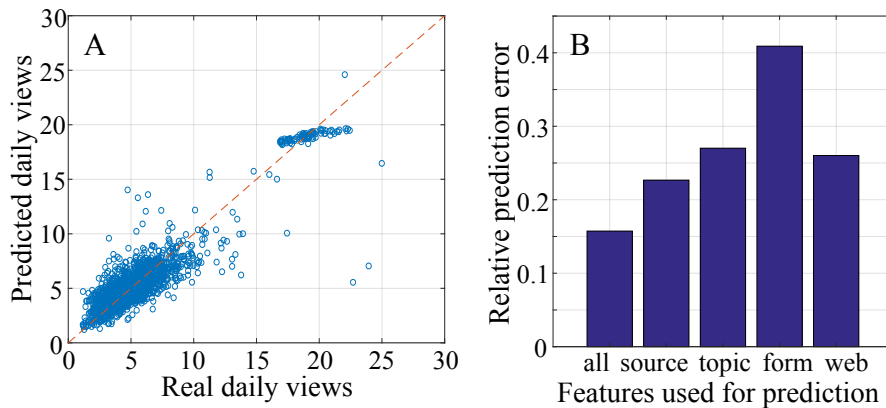


Figure 2: Popularity prediction when different classes of features are considered. (A) Real and predicted daily views for each document when all features are considered in the sparse linear regression model. Out-of-sample prediction based on 10-fold cross validation. The concentration along the diagonal indicates a good fit of the model. (B) Prediction error (10-fold cross validation) when using different sets of features.

204 3.2 Popularity and counterterrorism

205 We analyze how the popularity of documents is temporarily affected by coun-
 206 terterrorism operations. Other scholars have debated whether counterterrorism
 207 targeting affects the strategic success of terrorist groups [17, 18, 19, 20], but
 208 there has been less attention to the impact of targeting on the popularity of
 209 terrorists’ ideas and propaganda. We identify 11 authors that were killed and
 210 19 that were captured in counterterrorism operations during the data collection
 211 window (Table S1). We test whether targeting made the documents of these
 212 authors more popular by comparing the page-view trends to other documents on
 213 the website using Bayesian structural time-series (BSTS) models [21]. To find
 214 appropriate comparison documents, we use Euclidean distance nearest-neighbor
 215 matching to identify control documents that have similar page-view trends in
 216 the 90 days prior to the targeting event (Materials and Methods).

217 We find that targeting causes spikes of interest as shown in Fig. 3A. Targeting
 218 results in approximately 17 additional page views on the day after targeting,
 219 accumulating on average to 37 additional page views by the tenth day after
 220 targeting. This effect is driven almost entirely by targeted killings, rather than
 221 captures. Each document by a killed jihadist author gets an average of 26
 222 additional page views the day after targeting. This effect quickly fades, with
 223 no additional page views attributable to the targeted killing after about 10
 224 days. Cumulatively, targeted killings result in an average of 55 page views.
 225 Thus, the 11 authors killed during the period of data collection resulted in
 226 approximately 10,700 additional page views (since these 11 authors collectively
 227 wrote 195 documents). In contrast, the capture of jihadist authors has, on

228 average, little effect in days following their capture (Fig. 3C). The model predicts
229 6 additional page views for an author the day after capture, but this result is
230 not statistically significant at conventional levels.

231 Usama Bin Laden’s death is particularly relevant because there were con-
232 cerns that his death would result in renewed interest in his ideas [8, 9, 10].
233 Looking only at the 33 documents authored by Bin Laden, we find that his
234 death caused approximately 6,250 additional page views. Among the eleven
235 authors who were killed, seven experience significant increases in page views
236 following their death: Bin Laden (approximately 200 additional page views per
237 document), Abd al-Majeed Abd al-Majid (125 per document), Abu Yahya al-
238 Libi (70 per document), Anwar al-Awlaki (40 per document), Atiyya Allah (35
239 per document), Abu al-Walid al-Ansary (8 per document), and Khalid Abd al-
240 Rahman al-Husaynan (4 per document). Thus, not every targeted killing results
241 in more page views for the author’s writings, but many do. For all targets, the
242 spike in interest is temporary.

243 Are jihadists more interested in targeted authors because they see them as
244 martyrs? Or are these spikes simply due to news cycle visibility? The evidence
245 suggests that visibility, more than martyrdom, explains these results. All effects
246 we observe are short-lived, and match the duration of news cycle bursts [22].
247 If social constructions of martyrdom were causing these effects, we expect that
248 targeted killing would result in similar spikes for all authors. If publicity is the
249 cause, then popular authors will have bigger effects because their deaths are
250 more newsworthy. We find that the effects of targeted killing are much larger
251 for previously popular authors (Fig. S6).

252 False reports of targeting and failed attempts can also differentiate between
253 the effects of visibility and martyrdom, as these events create visibility for au-
254 thors without making them martyrs. We examine 4 cases of falsely reported tar-
255 geting and attempted targeting and find detectable spikes in popularity, though
256 they are smaller and shorter in duration (Fig. 3D).

257 A final way of separating publicity effects from martyrdom effects is to look
258 at natural deaths, which can also create publicity but do not theologically ele-
259 vate the status of the deceased to that of martyr. In the Figs. 3E-F we report
260 estimates of the effects of natural death. Fig. 3F shows that the natural death
261 of Rifa’i Surur caused his 9 documents to be viewed 1,500 more times per doc-
262 ument, given by the cumulative effect over the first ten days after his death. In
263 contrast, Fig. 3E shows that the other natural deaths during this time period
264 have no detectable effect on the popularity of the deceased. The likely cause
265 of the burst in popularity for Rifa’i Surur is that he was eulogized by several
266 prominent jihadists, including Muhammad al-Zawahiri (brother of Ayman al-
267 Zawahiri, current leader of Al-Qaeda). If famous ideologues can have spikes in
268 popularity after dying naturally as well as unnaturally, then fears that target-
269 ing will re-popularize jihadists ideas should not be an overwhelming concern for
270 counterterrorism policy makers.

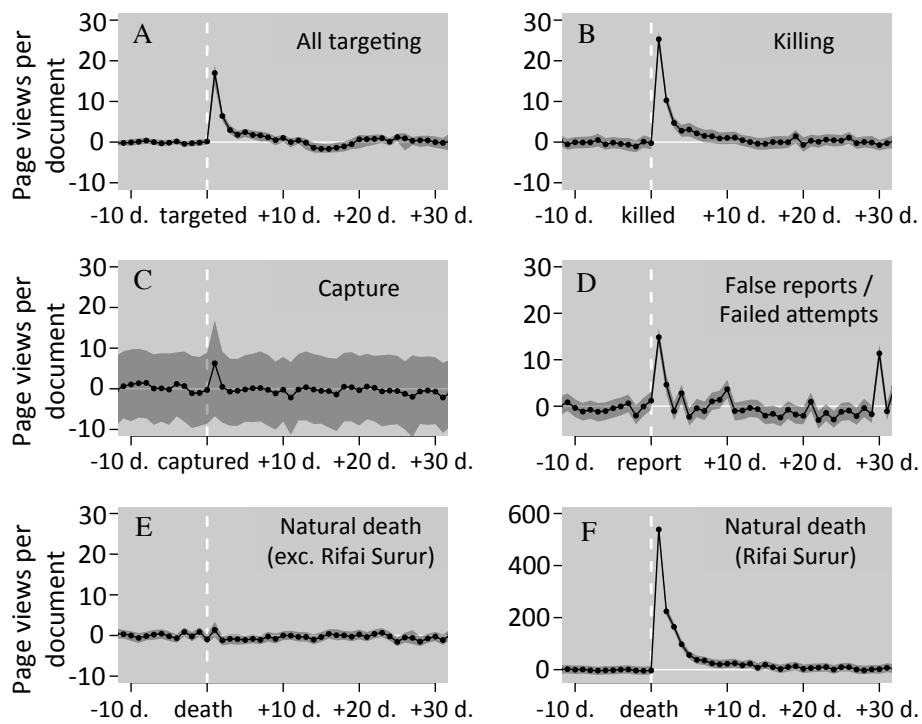


Figure 3: Effects of counterterrorism targeting on the popularity of jihadist texts. Estimated changes in the page views per document for documents of authors that were (A) targeted in any way (30 authors with 362 documents), (B) killed (11 authors with 195 documents), (C) captured (19 authors with 167 documents), (D) falsely reported to be killed or captured (4 authors with 12 documents), (E) died of natural causes, excluding Rifa'i Surur (12 authors with 61 documents), and (F) Rifa'i Surur's natural death (1 author, 9 documents).

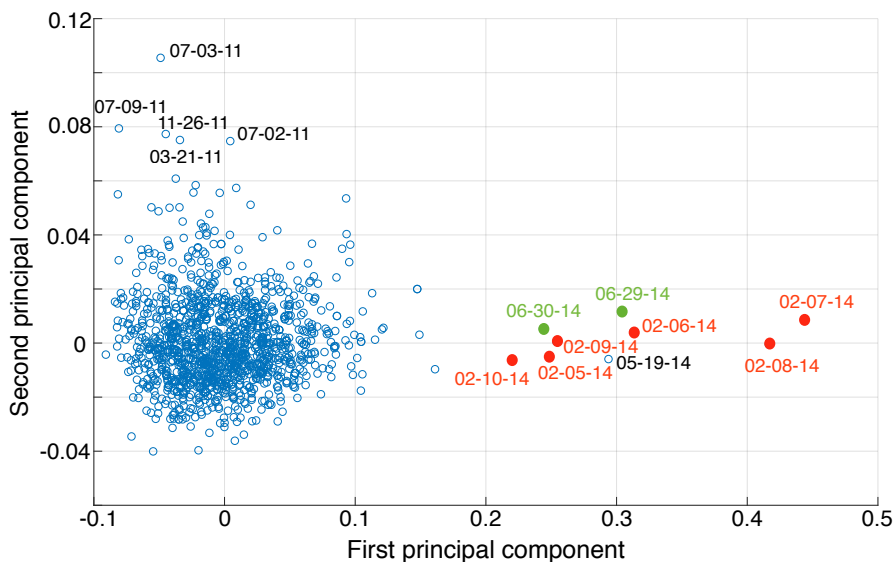


Figure 4: Effect of global events on popularity of jihadist texts. Principal component representation of the dataset. Al-Qaeda’s disownment of ISIS (Feb. 3rd 2014) and the declaration of the new Islamic caliphate (June 29th 2014) are possible explanations for the outliers marked in red and green, respectively.

271 3.3 Popularity and global events

272 Global events – not directly related to a specific author – also have temporary
 273 effects on the popularity of jihadist documents. More specifically, viewership
 274 interests can temporarily shift in response to global political events. To detect
 275 these effects we run a principal component analysis (PCA) [23] of the daily
 276 aggregated viewership of each author. We focus on the cleaned time series of
 277 the 5,227 documents that were present in the repository throughout the whole
 278 period of study. For each day, we aggregate the views per author in order to
 279 obtain a time series of total views for each author. We then perform a transversal
 280 normalization where we divide the views of each author in a given day by
 281 the total views of that day. The rationale behind this normalization is that we
 282 want to capture shifts in relative popularity between authors and not a global
 283 increase in popularity of the whole website. We can then think of each date
 284 as being a high-dimensional point with 775 features corresponding to the relative
 285 popularity of the 775 authors of the documents under study (excluding the
 286 empty’ author). Using PCA we project every high-dimensional point into the
 287 space spanned by the two principal components; see Fig. 4. The first principal
 288 component is dominated by the viewership of Sayyid Qutb – concentrating
 289 97.6% of the total energy – whereas the second principal component is dominated
 290 by the viewership of Abu Muhammad al-Maqdisi and Hani al-Saba’I –
 291 concentrating 80.6% and 12.8% of the total energy, respectively. In this way, an
 292 unusually large value of the first principal component for a given date translates

293 into an extraordinary relative interest in Qutb’s writings.

294 Most dates follow a common pattern of popularity concentrated around the
295 origin of the low-dimensional representation. All dates achieving an unusual pro-
296 portion of the second principal component occurred during 2011, corresponding
297 to key dates in the Arab spring [24, 25]. For dates achieving high values of the
298 first principal component, we find that Al-Qaeda’s disownment of ISIS (Feb.
299 3rd 2014) [26, 27] and the declaration of the new Islamic caliphate (June 29th
300 2014) [28, 29] are possible explanations for the outliers marked in red and green
301 in Fig. 4, respectively. We found that most of the interest in Sayyid Qutb that
302 spiked during these days was concentrated on his Quran commentary, suggesting
303 that these events might have caused interest in the doctrinally-oriented writings
304 of a prominent jihadist thinker.

305 4 Correspondence with the Popularity of Aca- 306 demic Manuscripts

307 We show evidence of a correspondence between the pattern of page views for
308 jihadist documents with the pattern of Twitter mentions and page views for
309 academic documents in an online preprint repository called arXiv². This cor-
310 respondence suggests that the total views that a document accrues within *The*
311 *Pulpit of Monotheism and Jihad* come roughly from two sources: a true interest
312 in jihadist authors and their new ideas – akin to novel academic papers in arXiv
313 combined with ephemeral spikes of general interest triggered by news cycles –
314 akin to Twitter mentions of academic articles.

315 The arXiv online repository makes scholarly papers in Physics, Engineer-
316 ing, and other scientific disciplines publicly available, thus promoting a rapid
317 dissemination of ideas. We examine two ways that people interact with papers
318 on arXiv: by downloading them (presumably to read and learn from them)
319 and by posting about them on the social media platform Twitter (presumably
320 because they are newsworthy). These two types of interactions happen on no-
321 ticeably different timescales. To test this, we rely on arXiv data from an existing
322 study [30] to compute the normalized cumulative views and Twitter mentions
323 of a newly uploaded manuscript. More precisely, for every new arXiv docu-
324 ment considered, we plot the cumulative downloads for the first 8 weeks as a
325 fraction of the total downloads accumulated by that document in the first 8
326 weeks; see Fig. 5A and Materials and Methods for more details. The red curve
327 in Fig. 5A corresponds to the median plot of the cumulative downloads among
328 the 195 documents considered, whereas the confidence intervals are drawn at
329 the 25th and 75th percentiles. We repeat the same procedure but for Twitter
330 mentions (instead of arXiv downloads) to obtain the green curve in Fig. 5A.
331 Twitter mentions follow a news-cycle timescale of approximately one or two
332 weeks. Individuals become aware of a paper when it is posted and tweet about
333 it if it is newsworthy to their social network. This gives rise to a fast-spreading

²Available at <https://arxiv.org/>.

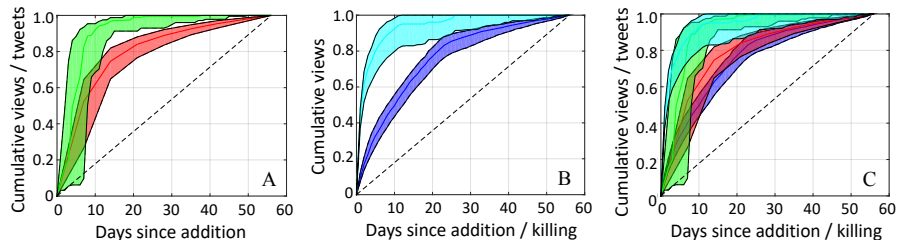


Figure 5: Normalized cumulative views and tweets for arXiv manuscripts and jihadist texts. (A) For a series of manuscripts uploaded to arXiv, we see the normalized cumulative views (red) and tweets (green) during the first 8 weeks after being uploaded. (B) In blue we have the normalized cumulative views of new jihadist texts during the first 8 weeks after being uploaded and in cyan we observe the cumulative views attributable to killings of jihadist authors during the first 8 weeks after the killings. (C) Superposition of the previous two figures revealing a remarkable resemblance between views of new arXiv manuscripts and jihadist texts on one hand and tweets about arXiv manuscripts and additional views attributable to killings of jihadists on the other hand.

334 and short-lasting presence in Twitter. Indeed, Fig. 5A shows that of all the
 335 tweets associated with a paper during its first two months after posting, 90%
 336 occur during the first 10 days. In contrast, the download patterns of papers
 337 follow a slower timescale. Many people download a paper when it first becomes
 338 available, after which there is a natural drop in viewing rates. However, there
 339 is a (sometimes sizable) residual activity presumably driven by readers truly
 340 interested in the ideas. Consequently, in Fig. 5A we see that only 60% of the
 341 paper downloads during the first 8 weeks are concentrated in the first 10 days.

342 We repeat the above experiment but for the views of new documents posted
 343 on *The Pulpit of Monotheism and Jihad* and for the views of jihadist texts
 344 attributable to targeted killings. More precisely, the blue curve in Fig. 5B cor-
 345 responds to the median curve of cumulative views during the first 8 weeks of
 346 new jihadist texts with confidence intervals given by the 25th and 75th per-
 347 centiles. The cyan curve in Fig. 5B represents the normalized cumulative views
 348 attributable to a targeted killing for the days directly following the killing. As
 349 expected, these latter views fade out more quickly, i.e., a sizable proportion
 350 (around 90%) of the views accumulated during the first 8 weeks after killings is
 351 concentrated on the first 10 days.

352 In Fig. 5C we superimpose the viewing patterns of arXiv manuscripts (Fig. 5A)
 353 and jihadist texts (Fig. 5B) and find remarkable similarities. Indeed, we find
 354 that the timing of page views for new documents posted on *The Pulpit of*
 355 *Monotheism and Jihad* almost perfectly matches the pattern of arXiv down-
 356 loads. More precisely, there is an initial spike of interest driven by novelty that
 357 then reduces to a steady-state viewership of people presumably interested in the
 358 ideas. By contrast, the views of jihadist texts attributable to targeted killings
 359 closely matches the Twitter mentions of academic papers. This further sup-

360 ports our argument that visibility, more than martyrdom, is what drives the
361 additional views. In this sense, the access to these texts is less ideologically
362 driven and, hence, less concerning.

363 5 Conclusion

364 What makes a jihadist text popular? Our study reveals that authorship – more
365 than topic – drives the steady-state popularity of jihadist writings. We also find
366 that external events change viewing patterns. Counterterrorism events tem-
367 porarily increase the popularity of jihadist authors by increasing publicity, but
368 we find no long-term effects in popularity. There is also an intriguing correlation
369 between key dates in the development of the Islamic State and views of Sayyid
370 Qutb’s writings. Together, these findings suggest that a logic of authority best
371 explains the steady-state popularity of jihadist documents. Newsworthiness
372 does matter, especially when a jihadist author becomes newsworthy on account
373 of his death in a counterterrorism activity. But these temporary publicity effects
374 due to targeted killings are relatively small and very short-lived. On one hand,
375 this alleviates concerns by some that capturing and killing jihadist writers in-
376 advertently repopularizes their ideas by making them into martyrs. We find no
377 evidence to support this claim. However, our results suggest that the steady-
378 state page views on the jihadist website we examine are best explained by a
379 logic of authority. This is concerning given that the documents that readers are
380 accessing often advocate political violence. Our findings show that targeting
381 popular authors with counterterrorism action does not induce any detectable
382 decline in their popularity.

383 On a broader level, we find a correspondence between the time-scales on
384 which texts are accessed in two very different domains: the jihadist web library
385 and the arXiv scientific repository. We conclude from this that the logics of
386 authority and newsworthiness we posit to explain viewership of jihadist texts
387 are also operating in the context of academic scientific discovery. Having a
388 better comprehension of the consumption patterns of jihadist texts opens a
389 window into the jihadist psyche, which may lead to the understanding of how
390 their thinking is shaped.

391 6 Materials and methods

392 Data cleaning

393 Two cleaning procedures were applied to the data of cumulative views: i) impu-
394 tation of missing data, and ii) outlier detection. For the imputation of missing
395 data, we linearly interpolate the curves of cumulative views for each document.
396 For example, if for a specific document we do not have view data for 20 days and
397 the next available data point records an increase in cumulative views of 1,000
398 clicks, we distribute these views equally and assume that each of the 20 days
399 contributed 50 views to the total. In terms of outlier detection, the objective is

Table 1: Features considered in the linear regression model

Feature	Class	Type	Description
Author indicator	Source	$\{0, 1\}$	One indicator variable per author
Explicit author	Source	$\{0, 1\}$	Indicates whether the author is stated explicitly in the website
Magazine indicator	Source	$\{0, 1\}$	One indicator variable per magazine
Topic model	Topic	$[0, 1]^{50}$	Proportion of topics in text (50 topics; see SI Appendix, Table S1)
Words in title	Topic	$\{0, 1\}$	Indicates words on title (Only for words appearing at least 15 times)
Length	Form	\mathbb{Z}	Number of words in the document
Log Length	Form	\mathbb{R}	Natural logarithm of Length
Nr Title Words	Form	\mathbb{Z}	Number of words in the title
Nr Title Chars	Form	\mathbb{Z}	Number of characters in the title
In Series	Form	$\{0, 1\}$	Indicates if the document belongs to a series of related texts
Common Text	Form	$[0, 1]$	Proportion of words used in the text that are common in Arabic
Common Title	Form	$[0, 1]$	Proportion of words used in the title that are common in Arabic
Lines Poetry	Form	\mathbb{Z}	Number of lines of poetry in the text
Lines Poetry Rel.	Form	\mathbb{R}	Lines Poetry divided by Length
Number webpages	Website	\mathbb{Z}	Number of subpages in the website in which the document appears
Rank	Website	\mathbb{Z}	Position in the list of documents of the same author
Log Rank	Website	\mathbb{R}	Natural logarithm of Rank
Rank Relative	Website	$[0, 1]$	Rank divided by nr of docs by author
Log Rank Relative	Website	\mathbb{R}	Natural logarithm of Rank Relative
Homepage days	Website	\mathbb{R}	Number of days spent in homepage
Log Homepage	Website	\mathbb{R}	Natural log of $(1 + \text{Homepage days})$
Homepage binary	Website	$\{0, 1\}$	Indicator if Homepage days > 200
Shortest Path	Website	\mathbb{Z}	Minimum nr of hyperlinks from the homepage to the document's page
Parent Page	Website	$\{0, 1\}$	Indicates parent page from which the doc can be indirectly accessed. Parent pages have shortest path of 1

400 to discard dates that record spurious, isolated, and out-of-scale view counts for
401 specific documents. These outliers are most likely attributable to either website
402 malfunctions or changes introduced by the webpage administrator rather than
403 actual views of interested readers. In order to detect such outliers, we perform
404 the following procedure: The difference between cumulative clicks of consecu-
405 tive days is computed in order to obtain a time series of daily clicks for each
406 document. For each of these time series, we slide a moving window of half-width
407 10 and compare the center value of the window with the median value within
408 the sliding window. If the center value is more than 15 times the median – thus,
409 presumably an outlier – we replace the center value by the median, otherwise
410 we leave it unchanged. In Fig. S7 we illustrate the cleaning procedure on a spe-
411 cific document (The Religion of Abraham and the Call of the Prophets and the
412 Messengers by Abu Muhammad al-Maqdisi), which is among the most popular
413 ones.

414 **Topic modeling**

415 We identify fifty topics and the proportion of each of these topics that a docu-
416 ment contains is used as a feature for our sparse linear regression method; see
417 Table 1. The topics are identified using supervised latent Dirichlet allocation
418 (sLDA) [31]. To be more concrete, we use the set of 1220 documents with-
419 out source no author or magazine features to train the best predictive topics.
420 Notice that for this set of documents we have all the words contained in each
421 document and a rate of daily views. Thus, we run an established sLDA package
422 for Python to infer latent topics predictive of the daily views³. Our code making
423 use of this sLDA package is also made available; see Data availability.

424 The most common words associated with each of the 50 topics recovered
425 are listed in Table S2. The topics are coherent and interpretable; for example,
426 topics 10, 15, 25, and 46 are about geopolitics and war, while topics 35, 37, and
427 38 are about traditional Islamic legal scholarship. Once the set of 50 topics is
428 determined, these are used to generate the topic features for all the remaining
429 documents. It becomes apparent that different authors are more commonly
430 associated with distinctive topics; see Fig. S8. Finally, from a procedural
431 perspective, notice that the texts without source are not used in our popularity
432 prediction analysis since they lack a source feature. This makes them the perfect
433 candidates to train the sLDA, thus allowing to train the features and test their
434 explanatory power on non-intersecting sets of texts.

435 **Popularity prediction via sparse linear regression**

436 Out of the 5,227 documents that were present in the repository during the
437 whole period of study, we have metadata available – thus, we can construct the
438 features in Table 1 – for 5,191 documents. Given that we want to test, among
439 other things, the effect that authorship has on the popularity of a document,

³The package used is available at <https://github.com/Savvysherpa/slda>.

440 we remove the documents with no source features. In terms of metadata, this
 441 means that we discard the documents with empty author that do not belong
 442 to a magazine publication, resulting in 4,086 available documents. We further
 443 trim this set of documents by two processes that we call rare-source filtering and
 444 impulsive denoising. Both processes are controlled by a parameter that we then
 445 vary to ensure that the results found are robust with respect to these trimming
 446 processes.

In rare-source filtering we discard documents written by authors (or contained in magazines) with less than th_1 documents, where the threshold th_1 controls the aggressiveness of the filtering procedure. For example, if we choose $th_1 = 10$, the corpus of documents is reduced from 4,086 to 2,659. In order to implement our impulsive denoising procedure we solve the following optimization problem

$$\min_{\{\beta_0, \beta, \alpha\}} \|\mathbf{y} - \mathbf{1}\beta_0 - \mathbf{X}\beta - \alpha\|_2 + \gamma\|\alpha\|_1, \quad (1)$$

where \mathbf{y} is a vector containing the steady-state daily views of all documents and \mathbf{X} is a matrix containing all features. The objective function of the optimization problem is composed of two terms: The fit of the rate of popularity \mathbf{y} in terms of the linear model plus a free vector variable α and a regularizer that imposes a sparsity structure on α . We modify the relative weighting γ to obtain different sparsity levels in α , thus resulting in different fits; see Fig. S4A. To constitute our corpus of relevant texts, we discard the documents for which the corresponding elements in α are different from zero. The parameter γ naturally regulates the level of denoising, e.g., if we set $\gamma = 10^{-1.5}$ we have that 12.6% of the documents get filtered, thus obtaining a final corpus of 2,324 texts on which to perform the popularity prediction. Once we have delineated the corpus of documents to be considered, we obtain the regression coefficients β via a cross-validated LASSO method [16]. More precisely, denoting by N the total number of documents considered, we seek to minimize the objective

$$\min_{\{\beta_0, \beta\}} \frac{1}{2N} \|\mathbf{y} - \mathbf{1}\beta_0 - \mathbf{X}\beta\|_2^2 + \lambda\|\beta\|_1, \quad (2)$$

447 composed of a fitting term and a sparsity regularizer on β that plays the double
 448 role of selecting the most important features and avoiding overfitting. The
 449 relative weight λ is selected via 10-fold cross validation; see Fig. S4B. In the Supplementary Material we report the prediction performance of the above sparse
 450 linear regression for different values of th_1 and γ , and when considering various
 451 subsets of features (Fig. S5).
 452

453 **Effect of counterterrorism on the popularity of texts**

454 Thirty-six authors with 426 documents were targeted (Table S1), but we only
 455 consider 33 of these authors (372 documents) because the remaining three authors
 456 were targeted too close to the end of the period of study to have sufficient
 457 data afterwards. In most cases, authors were targeted with either killing or capture,
 458 but we find instances of killing attempts that missed, and mistaken reports

459 of capture and killing where it was later revealed that the reported target was
460 still alive and free. A few individuals were targeted multiple times. We use the
461 page-view trends of the 372 documents produced by these targeted individuals
462 to test whether targeting increases interest in jihadist ideologues.

463 Inferring whether targeting changed a document’s popularity requires a
464 counterfactual estimate of how popular each document would have been in the
465 absence of the targeting event. We construct this counterfactual estimate by
466 identifying documents with similar page-view trends to those that were tar-
467 geted. Requiring that documents have similar page-view trends prior to the
468 date of targeting allows us to condition on all causes of prior popularity with
469 a single variable. To identify documents with similar page views, we calculate
470 the trend similarity for 90 days prior to the targeting date for every document
471 on the website using Euclidean distance. Although this method of matching
472 trends is simple, it is quite effective; Euclidean distance performs better than
473 many other time-series distance metrics [32, 33]. To select matching docu-
474 ments, we identify the document that minimizes the distance to each treated
475 document. To estimate treatment effects, we use BSTS models, implemented
476 in the CausalImpact package in the R statistical language. The BSTS model
477 is designed to estimate the effects of interventions on a single time series using
478 one or more untreated time series as predictors. We have multiple treated docu-
479 ments in our models, so we combine them into a single time series by taking the
480 mean for each date. We use each of the control documents as the predictors in
481 the BSTS model. Complementary approaches based on a frequentist regression
482 framework as well as on the celebrated difference-in-differences estimator [34]
483 were pursued, confirming the results found via the BSTS model. The number
484 of additional views attributable to killings obtained from the BSTS model were
485 also used in the generation of Fig. 5B. The uncertainty intervals in this figure
486 correspond to 95% Bayesian credible intervals around the estimated cumula-
487 tive views attributable to counterterrorism targeting. More information can be
488 found in the Supplementary Material.

489 Cumulative views in arXiv and Twitter

490 We consider the cohort of 4,606 scientific articles that were analyzed in [30].
491 These articles were submitted to arXiv between October 2010 and May 2011.
492 We further trim this cohort by focusing on the 500 most popular articles, i.e.,
493 the ones that were downloaded the most during the period of study. Of these
494 500 articles, we kept the 195 articles whose first version was uploaded between
495 October 2010 and February 2011. First, the reason for focusing on first versions
496 is that we want the uploads to be truly new, as opposed to updates to existing
497 manuscripts. Second, the reason for constraining the dates between October
498 2010 and February 2011 is to ensure that we have 8 weeks of download data
499 after the manuscript was uploaded. We also relied on [30] for the tweet counts
500 of these papers. However, as expected, most papers do not have significant
501 presence in Twitter. For the Twitter plots, we focused on the 12 articles that
502 had more than 25 mentions in Twitter during the period of study and were

503 uploaded between October 2010 and February 2011.

504 **Data availability**

505 All the data and metadata, along with code (R, MATLAB, and Python) to
506 replicate the figures can be accessed⁴.

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Password: nhb_jihad. Upon a potential publication, the dataset will be made public.

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