Global and Local ISIS Propaganda

Travers Barclay Child [*] Kai Gehring [†]
Sarah Langlotz [‡] Austin L. Wright [§]

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Abstract

This paper examines the effectiveness of terrorist propaganda at influencing public opinion in a conflict setting. From 2015 until the present, we examine various propaganda activities by ISIS in Afghanistan, including the circulation of video/print material, radio broadcasts, graffiti, and night letters. We leverage unique military-sourced microdata on propaganda activities and public opinion. These data are supplemented with additional sources providing a rich array of district- and household-level characteristics. With supervised machine learning we build a prediction model for the emergence of ISIS propaganda across Afghanistan. We then invoke various identification strategies to measure the impact of local and global propaganda on public opinion towards ISIS. We identify the impact of local ISIS propaganda by exploiting the construction/destruction of an ISIS radio tower in East Afghanistan. We identify the local impact of global propaganda by exploiting the precise timing of video/print material release, relative to household survey dates.

[*] CEIBS, *t.b.child@ceibs.edu*
[†] University of Zurich, *mail@kai-gehring.net*
[‡] Georg-August University Goettingen, *sarah.langlotz@uni-goettingen.de*
[§] University of Chicago, *austinlw@uchicago.edu*
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1 Introduction

Following the emergence of the Islamic State of Iraq and Syria (ISIS) in 2014, the group enjoyed territorial conquests in Iraq, Syria, Libya, Nigeria, Egypt, and Afghanistan (Jones et al., 2017). The rise of ISIS in Afghanistan, from mid-2014 until the end of 2015, was followed by significant contraction throughout 2016. Nevertheless, between January 2017 and October 2018, ISIS conducted more than 84 attacks killing 819 civilians across 15 Afghan provinces (Center for Strategic and International Studies, 2018). ISIS attacks in Afghanistan still persist in late 2020, even within the centeral government's seat of power in Kabul (Clayton, 2018; Reuters Staff, 2020).

The survival of ISIS, like that of all terrorist organizations, is crucially dependent upon local support in their area of operation (Department of the Army, 2007). For its part, ISIS operates a vast network of global and local propaganda activities (see e.g., Gambhir, 2016). These include (but are not limited to): video distribution, magazine publication (print and online), and radio broadcasts. The extent to which these activities bear on household approval of ISIS across Afghanistan is the topic of our study.

To understand the local pattern of emergent ISIS propaganda activity, we build a prediction model leveraging supervised machine learning. For this exercise we assemble data on 190 district characteristics across various fields of influence (e.g. economic conditions, security, quality of institutions, geography, etc). By comparing the predictive power of distinct variable groups, we identify factors most relevant for the emergence of ISIS propaganda in Afghanistan. Our findings suggest that levels of economic and institutional development are not powerful predictors of propaganda targeting. Aid flows and combatant support, on the other hand, do meaningfully predict the spatial allocation of terrorist propaganda.

Following our descriptive work on the local targeting of ISIS propaganda, we examine its effectiveness. We find correlational evidence suggesting ISIS has successfully boosted their local image through these propaganda initiatives. In ongoing work, we significantly strengthen identification by locating an ISIS radio tower in East Afghanistan and calculating its spatial reach across three provinces. In particular, we conduct a panel analysis examining the impact of local ISIS propaganda activity on public opinion outcomes. Specifically, this approach uses an established identification strategy of leveraging topography to isolate exogenous variation in exposure to radio broadcasts (see e.g., Olken, 2009; DellaVigna, Enikolopov, Mironova, Petrova, and Zhuravskaya, 2014; Yanagizawa-Drott, 2014; Armand, Atwell, and Gomes, 2020). The construction of the ISIS radio provides an opportunity to identify the impact of local propaganda messaging on the opinions of households within the radio's catchment area. Next we examine the local impact of global propaganda strategies

- the release of video and print material online. We match the day of video/photo release with household interview dates to measure the short-term impact of global propaganda on household views within Afghanistan. Thus far our findings suggest this globally targeted material adversely affects opinions toward ISIS among Afghan households.

A growing literature has explored media persuasion and the effectiveness of propaganda. Previous research determined that the political slants of US newspapers are ineffective at influencing voter perceptions (Gerber, Karlan, and Bergan, 2009; Chiang and Knight, 2011; Gentzkow, Shapiro, and Sinkinson, 2011). On the other hand, bias in television media has been shown to influence political preferences under democracies (DellaVigna and Kaplan, 2007; Durante, Pinotti, and Tesei, 2019; Martin and Yurukoglu, 2017) and weak institutions (Enikolopov, Petrova, and Zhuravskaya, 2011; Knight and Tribin, 2019).

Propaganda efforts by nefarious actors have also been shown to influence political and ideological preferences, with extremely deleterious consequences. DellaVigna et al. (2014) show that exposure to nationalistic Serbian radio in Croatia contributed to ethnic extremism. Adena et al. (2015) document how Nazi radio facilitated party recruitment and the consolidation of dictatorship, while inciting anti-Semitism among the citizenry. Yanagizawa-Drott (2014) documents the role of radio broadcasts in exacerbating the Rwandan genocide. And Müller and Schwarz (2019) show that anti-refugee social media posts by the far-right AfD party led to violent hate crimes against refugees in Germany.

While the above studies focus on propaganda efforts of legitimate state and media actors, we contribute by examining propaganda by a terrorist organization. A nascent literature focuses on the success of counterinsurgency information campaigns at inducing defections (Armand, Atwell, and Gomes, 2020) and garnering intelligence (Sonin and Wright, 2019). Our paper complements this work by studying the flipside of the COIN – the effectiveness of terrorist propaganda. We identify the impact of global and local ISIS propaganda on political preferences and ideological extremism. We also explore the conditions (at district and household level) under which ISIS propaganda is more or less effective.

Notably, Mitts (2019) and Mitts, Phillips, and Walter (2021) have shown that ISIS attacks in Europe and online propaganda efforts contributed to greater online support for ISIS among global Twitter users. Our study is differentiated from these works by focussing on local support for ISIS *within the conflict theater* where they are based. As local support is crucial for the survival of any insurgent group, understanding the local success of terrorist information campaigns is of critical importance to governments, policymakers, and militaries in conflict settings. The continued emergence of radical insurgent groups with increasingly global presence further underscores the importance of this topic.

The remainder of this article is structured as follows. Section 2 introduces our data.

Section 3 develops a cross-sectional prediction model for local ISIS propaganda activity. Section 4 (5) examines examines the impact of local (global) propaganda on measures of domestic support. Finally, section 6 concludes.

2 Data

This project leverages a trove of unique granular data from Afghanistan. In the subsections below, we introduce the myriad sources of information drawn upon for our analysis.

2.1 Public opinion

We possess extensive public opinion poll data by virtue of a pilot data-sharing agreement with NATO. Since 2008 the military alliance has commissioned a local survey company (ACSOR) to conduct nationwide polls on a quarterly basis, gathering information on household opinions of security conditions and conflict actors. Our analysis thus far focuses on two main outcome variables from this questionnaire: (i) *"Do you think the arrival of Da'esh would be a good thing or a bad thing for Afghanistan?"*, and (ii) *"Does Da'esh respect the religion and traditions of Afghans?"*. Household responses are on a 5- and 4-point scale, respectively, and ordered such that higher values reflect greater tacit approval of ISIS. Time series of nationwide average responses to these questions are depicted in Figure 1. Descriptive statistics for all variables in our analysis are provided in Table 1.

2.2 ISIS activity

2.2.1 Local propaganda

The abovementioned ANQAR survey data also contain information on the extent of local ISIS propaganda known to households. From March 2015 onward, the ANQAR survey asked households whether they witnessed any of the following activity by ISIS: publications (e.g. magazines or leaflets), radio broadcasts, black Da'esh flags or grafitti, and night letters.[1] From the survey responses we encode a binary household-level indicator for each type of activity. Then we construct a discrete count variable at the household level, reflecting the intensity of local ISIS activity known to that household by aggregating the abovementioned indicators. Figure 2 exhibits spatial variation in this measure of local ISIS propaganda by district during 2015, expressed in quartiles. Rather than being regionally concentrated, there

[1] The exact questionnaire phrasing was *"Have you heard of any of the following indicators of Da'esh activity in your mantaqa?"*

is surprisingly rich spatial variation in local ISIS propaganda across Afghanistan. Descriptive statistics are again offered in Table 1.

2.2.2 ISIS radio

Through qualitative research we identify the location and timing of an ISIS radio tower built and destroyed several times in East Afghanistan. Figure 1 reflects our knowledge thus far on the timing of events related to this tower. For periods of operation we construct a measure capturing the radio signal's reach in the region. We follow Yanagizawa-Drott (2014) and calculate the Longley-Rice model for radio propagation (Irregular Terrain Model, ITM). Based on descriptions of an earlier tower used by ISIS in Achin, Nangarhar, we estimate the height of the radio transmitter (antenna) as 30 feet. We use plausible values for portable transmitters (30 MHz at 300 Watts). Transmitters of this type would be fairly inexpensive and accessible. We estimate the location of the tower based on military records of an aerial bombardment that occurred in the district at the approximate time the radio went off the air. To calculate the ITM propagation, we follow Armand, Atwell, and Gomes (2020) and use the cloud-based platform CloudRF.com. We estimate the likely signal using a five foot receiver and a threshold of 25 dBuVm (at the recommendation of CloudRF's lead engineer). Figure 3 displays the outcome of the ITM with regions in red indicating signal exposure to the IS-K radio tower. Based on the distribution of radio reach we calculate two measures. First, we calculate the share of each district with signal exposure to the IS-K tower. Second, we create a population weighted measure. Population weights are derived based on the location and population of Afghan settlements from SEDAC. We weigh radio signal by the population that is exposed to the signal as a share of the total district population.

2.2.3 ISIS videos

To understand ISIS' global video propaganda activity, we rely primarily on the IntelCenter Database - a subscription platform cataloguing thousands of videos, audio clips, and pictures released by a number of terrorist groups, including ISIS.[2] We import data on 3,335 videos released between 2014 and 2018, including date of release, country of focus, language, and content keywords. Based on content keywords we further subdivide videos reflecting violence, state capacity, and religion. A time series for video types released by survey wave is provided in Figure A.1.[3] In a subsequent draft we plan to also incorporate thousands of still images

[2] Available at https://www.intelcenter.com.

[3] Some videos are tagged with vague content keywords precluding them from categorization. Those videos have been temporarily assigned to our smallest category - religion. In general, our present categorization is tentative in that we are in communication with IntelCenter regarding viable means of identifying video content.

accompanied with audio released by ISIS. Language and country breakdowns for both videos and stills are offered in Tables A.2 and A.3.

To supplement this primary measure of global video propaganda, we also build a list of 'popular' videos. For this we include those listed in the Wilson report (The Wilson Center, 2019), which contains a detailed list of events concerning ISIS from 2014–2018. We further include 'popular' videos discovered through our own online research. In gathering the latter, we checked for the following information: (i) the number of results obtained through a Google search of the video, and (ii) the number of news articles related to the video found in Factiva (filtering for five major journals: Al-Jazeera, Reuters, CNN, BBC and AP). Videos with at least 10 results in either Google or Factiva are regarded as having high media coverage. The time series for propaganda videos is presented in Figure A.2, where we distinguish between all videos reported by IntelCenter and popular videos fulfilling the abovementioned criteria.

2.3 Mobile Coverage

Vector data on mobile network coverage for GSM/2G and 3G is available from Collins Bartholomew (2021). This data includes all coverage areas reported to the company by April 2015.[4] GSM/2G refers to the second generation of mobile networks based on the Global System for Mobile Communications, while 3G refers to the third generation of wireless technology. 2G allows for voice call and message applications, whereas 3G (UMTS) enables video conferencing and mobile TV. Figure 4 displays mobile coverage based on GSM and 3G networks current for 2015. To construct a population-weighted measure of mobile coverage, we combine the network data with 2015 global population raster data from SEDAC. Population data is at a 30 arc-second resolution (equal to 1 km at the equator). We take the sum of all grid cells whose centroids are within a district boundary in order to calculate district population. Once the centroid of a 30 arc-second grid cell is within the polygon of either the 3G or GSM network coverage, we regard the population of this grid cell as having access to the signal. We then sum over grid cell populations in the coverage area, and divide by district population to yield the share of inhabitants with mobile coverage per district.

2.4 District and household characteristics

We collect district and household characteristics from a host of additional sources. First, we have obtained US military conflict data covering over 200,000 conflict events in theater since 2001. Second, we possess rare hardcopy data on the provision of aid in Afghanistan,

[4] For 3G, this is in fact the earliest data entry (i.e., prior to April 2015, no network operator submitted any information on 3G coverage to the company).

covering over 100,000 projects funded by 38 separate donors. Third, we obtained survey data on household vulnerability (NRVA) for 2005, 2007/8, and 2011. Fourth, we possess annual Asia Foundation survey data on public opinions across various domains of interest. Fifth, we have manually collected extensive measures of opium cultivability and production. Sixth, we leverage the ANQAR surveys for various household characteristics. And finally, we include additional piecemeal data on physical geographic characteristics, ethnicity, and more.

3 Spatial selection of local propaganda

Prior to exploring the effectiveness of ISIS propaganda at influencing local perceptions, we first examine the underlying spatial pattern of local propaganda activity. Accordingly, our analysis begins with a cross-sectional study of the correlates of local ISIS propaganda in Afghanistan. The outcome variable for this exercise is based on a composite measure of household-reported ISIS activity (see section 2.2.1). For each district sampled in 2015, we take the average response across households as our outcome for a cross-sectional prediction model. Figure 2 maps the spatial distribution of local propaganda, limited to the 317 districts for which covariate predictors are available.[5]

The academic literature to date offers little concrete guidance (theoretical or empirical) for constructing priors regarding determinants of terrorist propaganda. From the broader conflict literature we therefore identify eight potential 'fields of influence' which conceivably impact the local presence of ISIS. As broad conceptual categories, these are encapsulated by the following labels: combatant support, development aid, political/ideological preferences, crime and corruption, security conditions, economic conditions, quality of institutions, and (immutable) geography. For each of these domains we gather a host of distinct characteristics measured at the district level (see section 2.4). By combining these data sources, we produce a cross-sectional dataset covering 80% of Afghanistan's 398 districts. The cross-section is centered around 2010, and includes 190 district-level characteristics in total (listed by category in tables OA.1 – OA.8).

The breadth of theoretically sound determinants of ISIS activity far exceeds the amount of covariates feasibly accounted for with a standard regression model. We therefore adopt a supervised machine learning technique to narrow down our set of predictors. Specifically, we invoke the Lasso model which minimizes the sum of squared errors, but with a penalty

[5] At the district level, the mean of our composite measure for local propaganda is 0.8, whereas the minimum and maximum values are 0 and 3.4, respectively.

term added to reduce the absolute sum of coefficient magnitudes.[6] By penalizing coefficient magnitudes during optimization, the impact of many covariates is reduced to zero. The model's output therefore includes only the subset of covariates most important for predicting the emergence of local ISIS propaganda. These results are not to be interpreted causally, but they nevertheless shed light on potentially important factors related to ISIS targeting practices.

To gauge the importance of each field of influence, we develop the following approach combining insights from Bazzi et al. (2019) and Colonnelli, Gallego, and Prem (2020). First we predict ISIS intensity across all districts by using its nationwide empirical mean. The baseline $RMSE^0$ (root mean squared prediction error) associated with this prediction model is simply the standard deviation of the outcome. Next we invoke the Lasso to build a prediction model using covariates limited to a single field of influence c.[7] The corresponding $RMSE^c$ is calculated by comparing observed with predicted values of ISIS propaganda in each sample district. The difference ($RMSE^c$–$RMSE^0$) then serves as a measure of importance for the field of influence c. We recalculate this measure of importance for 2000 bootstrap samples.[8] Figure 5 illustrates the resulting distributions for the importance of each field of influence.

In Figure 5 we find security conditions collectively constitute the weakest field of influence on local ISIS propaganda. In other words, spatial targeting of propaganda efforts do not appear meaningfully driven by instability or conflict dynamics. We observe the strength of judicial/health/educational institutions as the second-least important field of influence, followed by local economic conditions. The level of development is therefore a relatively poor predictor of local ISIS propaganda activity. This finding suggests ISIS was not disproportionately targeting the underserved or underprivileged when attempting to leverage local support in Afghanistan. Corruption and crime are related to both institutional quality and security conditions, and this field of influence is also less important than fixed geographical character-

[6] Specifically, we optimize: $\min_{\beta,\lambda}\{\sum_{i=1}^{N} y_i - X_i\beta^2\}$ s.t. $\sum_{j=1}^{P}|\beta_j| \leq \lambda$, where j indexes P candidate predictors. The size of the penalty (λ) is chosen to minimize out-of-sample prediction error using 10-fold cross-validation.

[7] Following the optimization, only a subset of covariates within each field are selected as predictors.

[8] The resulting distribution of importance is a more reliable measure than individual covariate point estimates based on the original sample draw. As with many supervised machine learning prediction algorithms, the importance of individual covariates is quite sensitive to sample composition. See Figure 2 of Mullainathan and Spiess (2017) for a concrete illustration of this phenomenon.

istics.[9] Importantly, development aid and combatant support constitue the most important predictors of ISIS propaganda.[10] The latter finding suggests we need to carefully account for possible reverse causation when later estimating the impact of ISIS propaganda on measures of ISIS support. Interestingly, these field of influence (alongside geography) may additionally serve to amplify the effectiveness of terrorist propaganda (thereby justifying ISIS' spatial allocation according to these criteria). In sum, through this exercise we may attach (implicit or explicit) upper bounds on the importance of omitted variable bias from some fields of influence, highlight the suggested threat of reverse causation from combatant support, and reveal candidate sources of heterogeneity for the effectiveness of ISIS propaganda.

4 Local propaganda and local perceptions

As a first step in understanding how local ISIS propaganda influences domestic support for the group in Afghanistan, we test for cross-sectional correlations between awareness of local propaganda and public opinion outcomes. To this end we estimate:

$$Y_{idw} = \beta_0 + \beta_1 P_{idw} + \beta_2 X_{idw} + \delta_d + \omega_w + \epsilon_{idw} \tag{1}$$

Here Y_{idw} reflects the degree of ISIS support expressed by individual i in district d during survey wave w (see section 2.1 for detail on outcomes). P_{idw} captures local ISIS propaganda activity known to individual i (see section 2.2.1); X_{idw} constitute household controls (i.e. ethnicity, age, educational attainment, and income); δ and ω capture district and wave fixed effects; and errors (ϵ) are clustered at the district level.

To reflect the intensity of local ISIS activity, propaganda is measured as a discrete count variable in column 1 of Table 2. The results of that column suggest survey respondents aware of more local ISIS propaganda express greater approval for the group's arrival in Afghanistan. Columns 2-5 consider each propaganda activity (publications, radio broadcasts, black Da'esh flags, night letters) separately. The strong positive correlation from column 1 persists across all types of local propaganda. Columns 6-10 introduce our second measure of household support. Column 6 suggests households subject to greater local ISIS propaganda more strongly

9 We can calculate bounds for omitted variable bias related to fixed geographical characteristics by observing, for example, coefficient/R^2 movements when including district fixed effects in our panel analysis later on. That amount of bias may then constitute an upper bound for time-varying omitted variable bias from less important fields of influence revealed here (e.g. economic conditions, institutions, security). In a similar spirit, Bazzi et al. (2019) draw strong conclusions when comparing the predictive power of time invariant and (cross-sectional) time variant characteristics within a Lasso framework.

10 Recall our cross-sectional determinants are centered on 2010 while (in the present section) ISIS propaganda is measured for 2015.

believe ISIS respects the religion and traditions of Afghans. Again, the effect remains stable when we consider each activity separately in columns 7-10. The foregoing correlations are based on survey measures of propaganda awareness, however, and are therefore prone to subjective response bias (see e.g., Child and Nikolova, 2020).

4.1 Radio-tower in Nangarhar

To strengthen identification we next analyze the impact of local radio propaganda in Nangarhar. As described in section 2.2.2, we exploit information on an ISIS radio tower established (and subsequently destroyed) in the province. Although the location of the tower is not random, the strength of the radio signal reaching population settlements in the region can be considered exogenous and depends largely on the local topography/terrain. Based on our parameterization, the radio signal's reach is illustrated in Figure 3.

For our estimation we will use a difference-in-differences (DiD) approach based on the following model:

$$Y_{idw} = \beta_0 + \beta_1 T_i + \beta_2 P_w + \beta_3 T_i * P_w + \beta_4 X_{idw} + \delta_d + \omega_w + \epsilon_{idw} \tag{2}$$

where Y_{idw} reflects the degree of ISIS approval by individual i in district d interviewed in wave w; T_i indicates the household falls within broadcast range; and P_w indicates whether the radio was transmitting during wave w. The coefficient β_3 therefore captures our effect of interest (i.e. the impact of residing in the broadcast zone during a period of transmission). Presently we are attempting to resolve uncertainty surrounding the broadcast timeline depicted in Figure 1.

5 Global video release and local perceptions

Next we begin to explore differences in reception between locally targeted propaganda efforts (as above) and global media campaigns (as below). We begin this analysis by running a simple regression model investigating the impact of global video releases on household approval of ISIS. Notably, the online circulation of ISIS videos varies on a daily basis. We interact our measure of video release with cross-sectional variation in access to mobile networks. In this respect, we rely on information about mobile coverage from Collins Bartholomew (2021). As described in section 2.3, we calculate the share of district population with access to the 3G network which (among other applications) permits users to watch videos. We expect the exposure to global propaganda videos to be stronger among households inhabiting districts with 3G network coverage. Alternatively put, households are more likely to see propaganda videos when they live in an area falling within the 3G network. Our estimated model takes the form:

$$Y_{idtw} = \beta_0 + \beta_1 V_{tw} + \beta_2 M_d + \beta_3 M_d * V_{tw} + \beta_4 X_{idtw} + \delta_d + \omega_w + \epsilon_{idtw} \tag{3}$$

Here V_{tw} refers to the number of ISIS propaganda videos released in the month preceding interview day t of survey wave w.[11] Column 1 of Table 3 Panel A reports results from estimating equation 3, while columns 2 and 3 are presented for robustness. Column 2 serves to provide a potentially more suitable counterfactual by using only households with GSM network coverage as our reference category. By restricting our sample to districts with non-zero mobile coverage, we help control for the possibility that mobile adoption (and not 3G per se) is ultimately the source of any heterogeneous effects. Along similar lines, given the high correlation between mobile networks and economic development, in column 3 we allow the impact of ISIS videos to vary also according to nightlights. Columns 4–6 repeat the exercise for our second outcome of interest. In none of the table's columns do we find strong evidence for a differential impact of ISIS videos on attitudes towards ISIS among households with 3G access.[12]

In Panel B of Table 3 we replace the overall number of videos (reported by IntelCenter) with the number of popular videos according to our additional sources (see section 2.2.3). Interestingly, we find evidence that ISIS videos with popular global reach do in fact influence local perceptions in Afghanistan. Of note, however, in columns 1–3 the direction of impact runs *contrary* to local forms of propaganda activity by the same group. This discrepancy may emanate from diverging informational content across different target audiences (between local and global material). In column 5 however, we find evidence these videos still boost local perceptions of the group's consistency with Afghan traditions, even while dismaying citizens of the desirability of ISIS' emergence. Table B.2 reflects similar findings when aggregating videos over a longer two-month period. The negative impact of global video releases on local approval of ISIS is further explored below.

To strengthen identification we next investigate the short-term impact of global videos by exploiting the exact dates of video release and survey enumeration. Specifically, we use exact dates to associate each individual in our survey to the number of videos released the day before their interview. Accordingly, we specify the following model:

[11] We possess information on the exact date of each video release, and on the exact date of each interview.
[12] In effect, we obtain precisely estimated zeros in Panel A.

$$(4) \qquad Y_{idtw} = \beta_0 + \beta_1 V_{t-1} + \beta_2 V_t + \beta_3 V_{t+1} + \beta_4 X_{idtw} + \alpha_{dw} + \epsilon_{idtw}$$

Y_{idtw} again reflects the degree of ISIS approval by individual i in district d, interviewed on day t of wave w. V_t is the number of videos released by ISIS on day t.[13] X_{idtw} represents individual controls: age, gender, education and ethnicity. α_{dw} represents district-wave fixed effects. So we are comparing individuals surveyed during the same enumeration period with the same district, differentiated only by the number of videos released just prior to their interview. Finally, standard errors (ϵ) are clustered at the district level.

In column 1 of Table 4 we examine the next-day impact of global video releases on local perceptions of ISIS in Afghanistan. When more videos are released just prior to the survey enumeration date, respondents tend to report a lower approval rating for ISIS. In column 2, this effect holds conditional on controlling for videos released the day of (t) and the day after ($t+1$) interviews. Figure 6 further demonstrates that placebo event days immediately preceding our period of interest do not yield similar effects. In columns 3-4 we repeat the same exercise using instead a binary indicator for videos released each day. Our result is robust to this alternative formulation. Next in columns 5-8 we test the impact of video release on our alternative measure of local support, and find no significant effects.

To further unpack the significant finding above, we next explore heterogeneous effects by specifying the following model:

$$(5) \qquad Y_{idtw} = \beta_0 + \beta_1 V_{t-1} + \beta_2 H_{idtw} + \beta_3 V_{t-1} H_{idtw} + \beta_4 X_{idtw} + \alpha_{dw} + \epsilon_{idtw}$$

Here H_{idtw} represents a characteristic of interviewee i from district d (interviewed on day t of wave w). The coefficient β_3 captures effect heterogeneity along dimension H, while X_{idtw} again collects individual controls (with errors clustered by district).

Table 5 presents results for our heterogeneity tests across various characteristics of interest. Thus far we find no evidence to suggest the impact of global propaganda videos on local perceptions of ISIS varies according to age, gender, educational attainment, or ethnicity. Thus, in Table 6 we explore effect heterogeneity stemming from *district-level* characteristics. Here we invoke a model similar to equation 4 but with H varying only by district (hence – H_{dtw}). In columns 1-2 we find the impact of ISIS videos to be strongest in rural districts. In columns 4-5 we find ethnic fractionalization and polarization to mitigate the adverse impact of global propaganda efforts on local support for ISIS. The district-level variables in Table 6

[13] We drop the subscript w on V to simplify notation.

constitute geographical characteristics - an important field of influence explaining the spatial allocation of local ISIS propaganda activity (recall from section 3). Therefore it would be instructive to also test whether more important spatial predictors (i.e. development aid or combatant support) also serve to amplify the impact of global and local propaganda efforts.

Finally, following Mitts, Phillips, and Walter (2021) we separate videos into content categories. At present our classification relies on incomplete content keyword tags provided by IntelCenter Database, and the resulting distribution of videos across violent, state capacity, and religion categories is somewhat crude as a consequence. Nevertheless, we do find evidence consistent with Mitts, Phillips, and Walter (2021) in that violent videos appear to drive the negative impact on local support for ISIS. Tentative results are offered in Table B.3.

6 Conclusion

So far in this paper we examine the spatial correlates and public opinion consequences of terrorist propaganda. We leverage rich spatiotemporal data on public opinion, ISIS propaganda, and a host of district/household characteristics across Afghanistan. We introduce a prediction model to identify categories of influence closely related to the targeting of local propaganda activity (while also revealing relatively unimportant characteristics in this regard). Subsequently, we examine the impact of local and global ISIS propaganda on measures of local support within Afghanistan. We find that household approval measures increase during periods of greater local propaganda activity. However, the contrary appears true when examining the local impact of *globally* targeted propaganda initiatives.

In a subsequent draft we aim to identify the local conditions under which terrorist propaganda is more or less effective. In this respect we can leverage results from our prediction model in that strong predictors of propaganda activity may also serve as important sources of effect heterogeneity. We also plan to invoke video and photo microdata to enhance our theoretical contribution parsing local from global propaganda. In particular, we possess information on the language and target nation of ISIS videos, and this can be treated as an important factor distinguishing local from global messaging campaigns.

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Figure 1: Timeline ISIS information

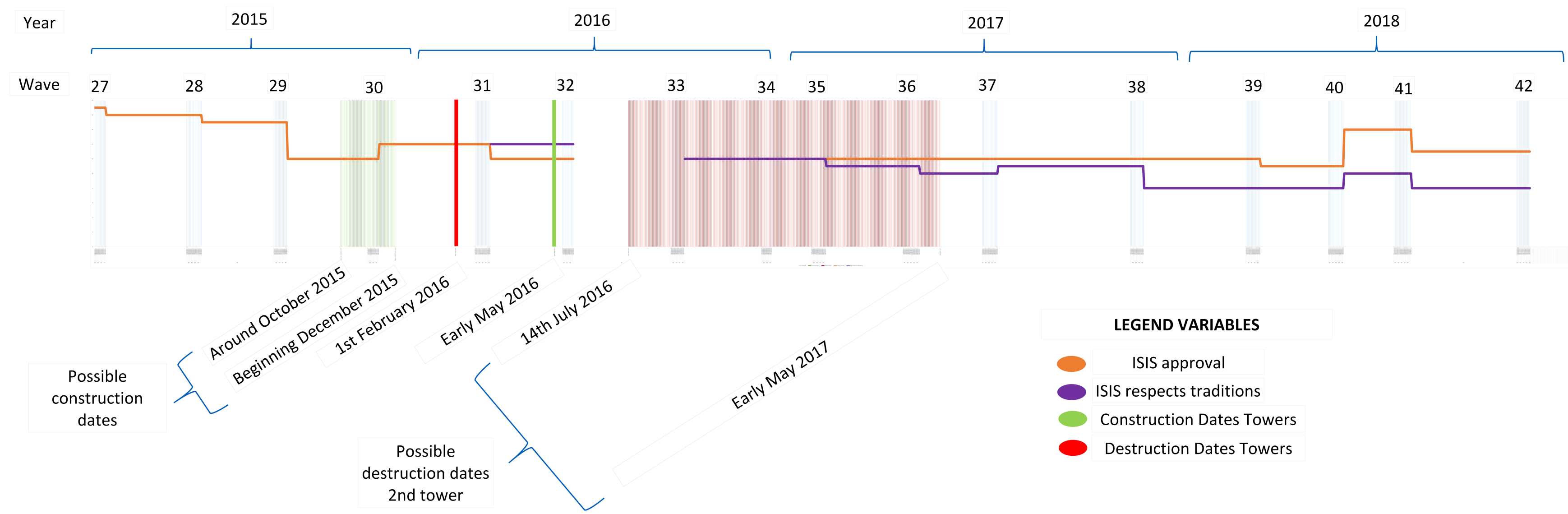
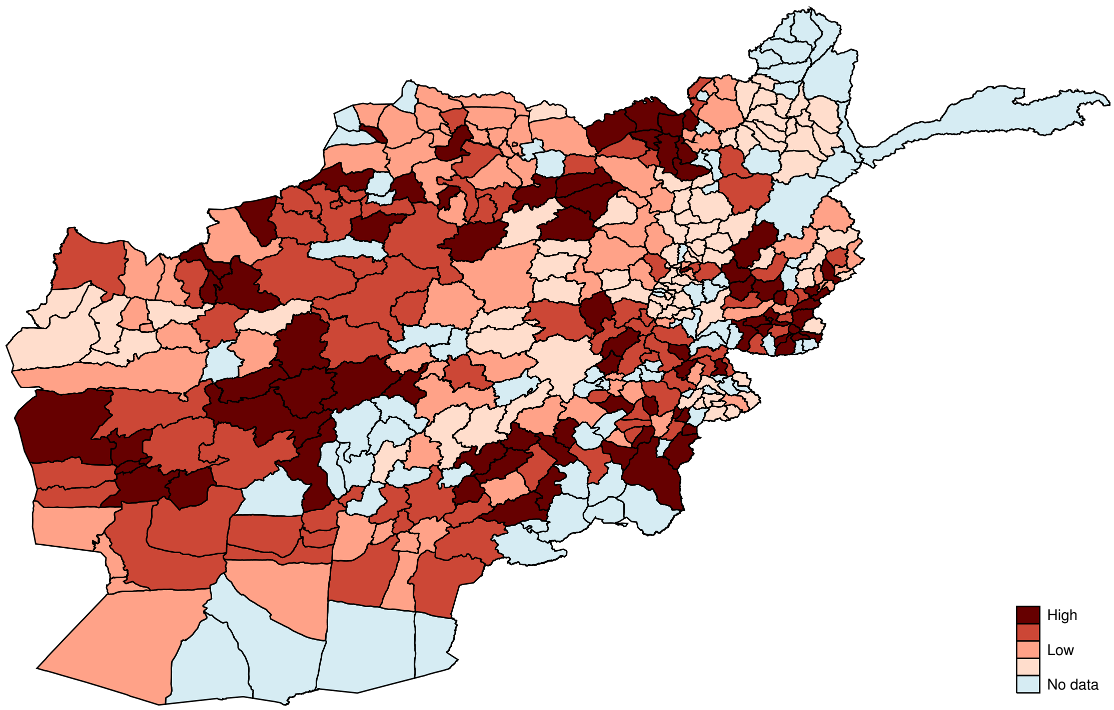
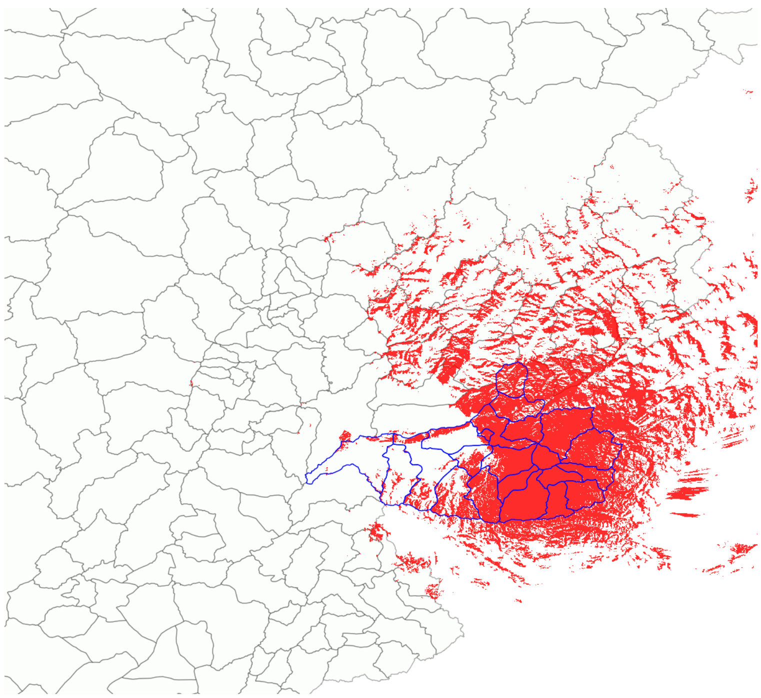


Figure 2: Spatial distribution of ISIS propaganda



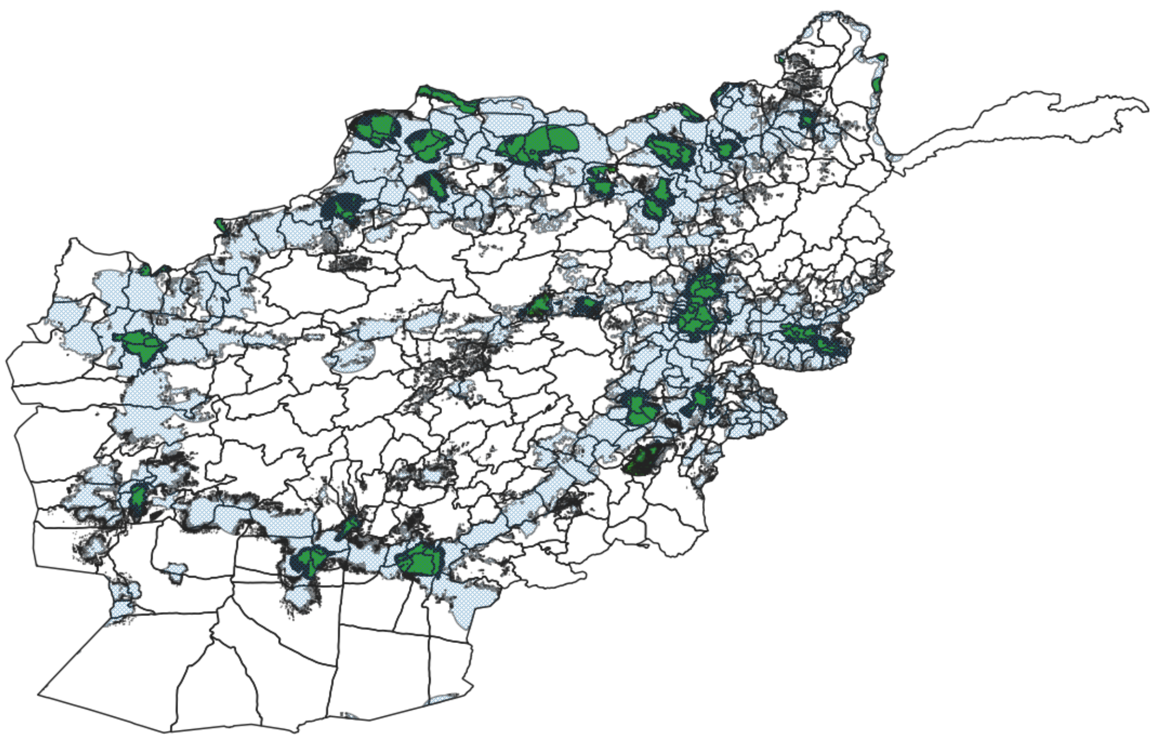
Notes: ISIS propaganda is constructed based on ANQAR survey responses. For each household we sum up the number of reported activities including graffiti, night letters, publications, and radio broadcasts. District averages are then calculated from all households sampled in 2015, and the corresponding quartiles are indicated in the figure. 80% (317) of Afghanistan's 398 districts are covered in our cross-sectional sample. The remaining 20% are excluded due to missing covariates. To arrive at our final sample, the following backward stepwise procedure is conducted. Beginning with no covariates and all 398 districts, we repeatedly include covariates with the broadest spatial coverage relative the current subsample. We stop adding covariates once doing so would reduce spatial coverage below 80%.

Figure 3: ISIS radio tower signal



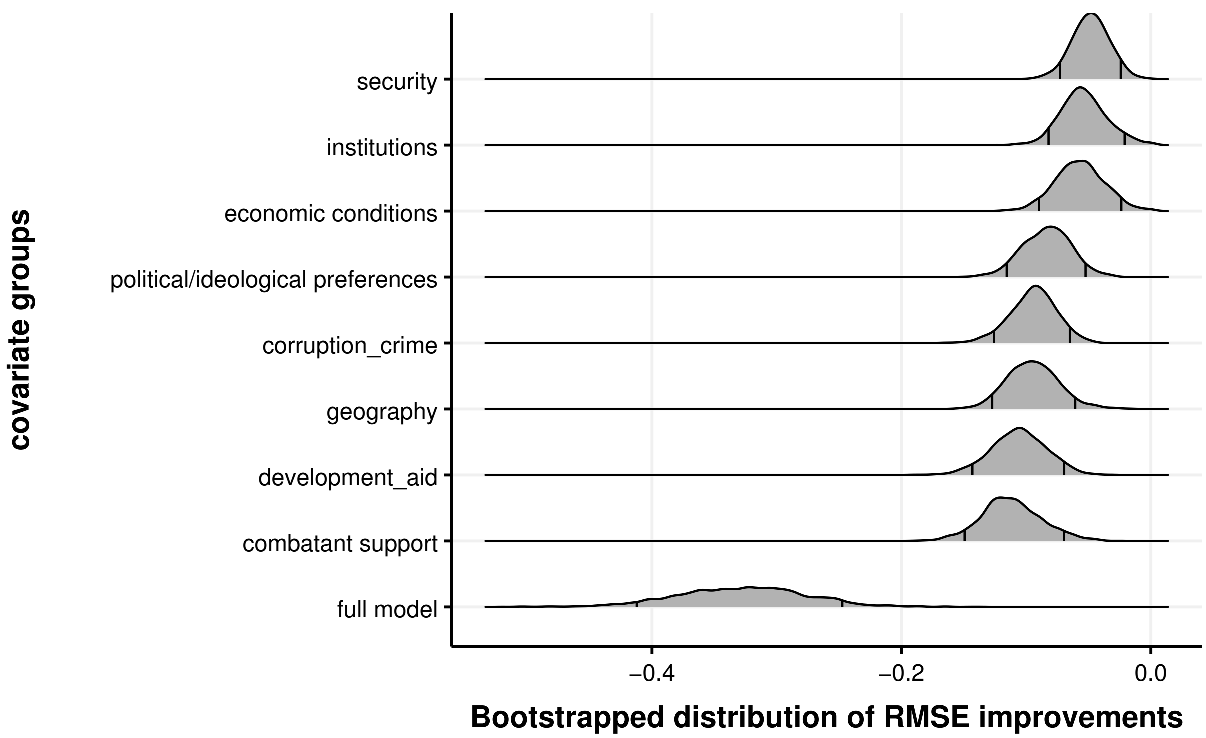
Notes: Original information on radio tower signal based on the ITM as explained in section 2.2.2. Areas in red indicate those with access to the radio signal by ISIS radio tower. Districts with blue boundaries belong to the province Nangahar, which is in the East of Afghanistan.

Figure 4: Mobile Network Coverage: GSM and 3G



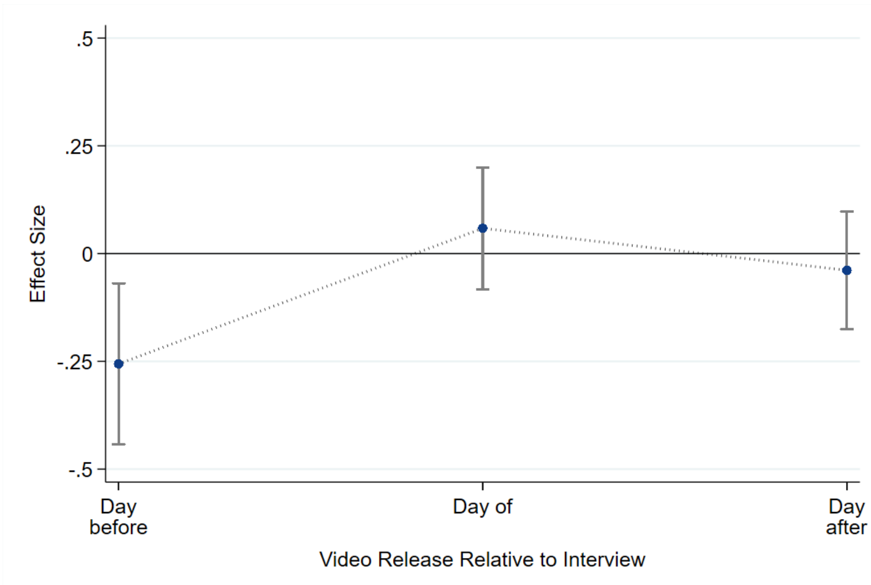
Notes: This map displays mobile network coverage based on data from Collins Bartholomew (2021) for the year 2015. Areas in light blue have access to GSM and areas in green have access to 3G. For more details, see section 2.3.

Figure 5: Contributions to Prediction Accuracy



Notes: This figure compares the importance of various fields of influence when predicting ISIS propaganda activity. Each row reflects the distribution of $RMSE^c - RMSE^0$ across 2000 bootstrap iterations. $RMSE^c$ is calculated from the Lasso model using covariates from category c labelled in the corresponding row. $RMSE^0$ is based on predictions using the observed empirical mean (0.8). Notches mark the 5% most extreme observations at each end of the distribution.

Figure 6: Coefficients Plot: Propaganda Videos



Notes: Graph displays model 4 including the contemporaneous effect, one lead and one lag, illustrating results of table 4, column 2. Graph takes into account waves 28 to 33, included.

Table 1: Descritive Statistics

Panel A: Individual Level

	Summary Statistics				
	N	Mean	SD	Min	Max
Age	349350	34.95	12.45	18	99
Male	349350	0.62	0.48	0	1
Binary: Education	349350	0.43	0.50	0	1
Binary: Pashtun	349350	0.42	0.49	0	1
ISIS Arrival Approved	130519	11.10	20.98	0	100
ISIS Respects Traditions	129447	9.15	19.90	0	100
Local Propaganda	87575	0.61	0.97	0	4
Black Flag	87423	0.22	0.42	0	1
Night Letters	87109	0.10	0.30	0	1
Publication	87290	0.18	0.38	0	1
Radio Broadcasts	87177	0.12	0.32	0	1

Panel B: District Level

	Summary Statistics				
	N	Mean	SD	Min	Max
Close City	349350	0.30	0.46	0	1
Urbanization	346698	0.20	0.36	0	1
Fractionalization	349350	0.29	0.25	0	1
Polarization	349350	0.43	0.34	0	1
Nightlight data per district	349350	5.40	13.29	0	46
Opium	324622	0.03	0.11	0	1
3G	349350	32.82	42.97	0	100
GSM	349350	74.66	35.42	0	100
Radio Signal	349350	1.42	2.56	0	10

Panel C: Videos

	Summary Statistics				
	N	Mean	SD	Min	Max
Videos	236474	1.91	2.48	0	12
Videos (religious)	236474	0.00	0.05	0	1
Videos (violence)	236474	1.37	1.95	0	9
Videos (state capacity)	236474	0.33	0.69	0	4
Binary: Videos	236474	0.64	0.48	0	1
Popular Videos	236474	0.03	0.18	0	1

Table 2: Local propaganda and ISIS approval

	ISIS Approval					ISIS Respects Traditions				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Local Propaganda	2.228***					1.188***				
	(0.294)					(0.323)				
Black Flag		3.875***					1.812***			
		(0.596)					(0.661)			
Night Letters			4.591***					2.543***		
			(0.762)					(0.675)		
Publication				1.618***					1.188*	
				(0.413)					(0.639)	
Radio Broadcasts					4.169***					1.838**
					(0.645)					(0.836)
Observations	85427	85281	84984	85158	85049	37640	37584	37477	37551	37520
Adjusted R^2	0.155	0.153	0.152	0.150	0.152	0.153	0.153	0.153	0.152	0.153

Notes: Table reports results of equation 1. Data on outcome (ISIS approval) available from 2015 to 2018 included. Outcome variable standardized in range [0,100]. Data on outcome (ISIS respects traditions) available from 2016 to 2018 included. Outcome variable standardized in range [0,100]. Analysis is based on events that happened in Afghanistan. Baseline controls include age, gender, education level and ethnic group. All models include district and time(wave) fixed effects. Standard errors in parentheses; clustered at the district level.
$*p < 0.10 ** p < 0.05 *** p < 0.01$

Table 3: Global Propaganda and ISIS Approval

[*Panel A*: Videos]

	ISIS Approval			ISIS Respects Traditions		
	(1)	(2)	(3)	(4)	(5)	(6)
Videos x 3G	-0.000	-0.000	-0.000*	-0.000**	0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Videos	0.066**	0.039	0.066**	-0.036	0.027	-0.037
	(0.027)	(0.030)	(0.027)	(0.034)	(0.033)	(0.034)
Videos x Nightlight			0.000*			0.000
			(0.000)			(0.000)
Observations	130461	75419	130461	129385	71287	129385
Adjusted R^2	0.126	0.078	0.126	0.116	0.111	0.116
Joint significance (p-value)	0.014	0.189	0.015	0.283	0.418	0.277

[*Panel B*: Popular Videos]

	ISIS Approval			ISIS Respects Traditions		
	(1)	(2)	(3)	(4)	(5)	(6)
Popular Videos x 3G	-0.014***	-0.012*	-0.013**	-0.003	0.017**	-0.002
	(0.004)	(0.007)	(0.006)	(0.005)	(0.007)	(0.007)
Popular Videos	0.757	-0.678	0.817	-0.020	-1.889**	-0.025
	(0.759)	(0.962)	(0.711)	(0.803)	(0.952)	(0.806)
Popular Videos x Nightlight			-0.003			-0.003
			(0.010)			(0.013)
Observations	130461	75419	130461	129385	71287	129385
Adjusted R^2	0.126	0.079	0.126	0.115	0.111	0.115
Joint significance (p-value)	0.325	0.472	0.256	0.977	0.050	0.973

Notes: Table reports results of equation 3. Columns 2 and 5 restrict sample for districts with some access to GSM. Data on outcome (ISIS approval) available from 2015 to 2018 included. Outcome variable standardized in range [0,100]. Data on outcome (ISIS respects traditions) available from 2016 to 2018 included. Outcome variable standardized in range [0,100]. 3G is a continuous variable indicating the share of population with mobile coverage (2015). Nighlight inidicates nightlight data per district (2011). Joint significance tests if Videos/Popular Videos (month before) + Videos/Popular Videos (month before) x 3G equal zero. Baseline controls include age, gender, education and ethnic group. All models include district and time(wave) fixed effects. Standard errors in parentheses; clustered at the district level.

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

Table 4: Within Wave: Impact on ISIS Approval

	ISIS Approval				ISIS Respects Traditions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Videos (t-1)	-0.274***	-0.254**			0.0820	0.0863		
	(0.0943)	(0.0988)			(0.0663)	(0.0698)		
Videos (t)		0.0672				-0.0139		
		(0.0805)				(0.0697)		
Videos (t+1)		-0.0182				-0.112		
		(0.0729)				(0.0953)		
Binary: Videos (t-1)			-0.607**	-0.602*			-0.115	-0.0739
			(0.307)	(0.329)			(0.303)	(0.300)
Binary: Videos (t)				0.0386				-0.0524
				(0.325)				(0.390)
Binary: Videos (t+1)				-0.202				-0.513*
				(0.384)				(0.284)
Observations	130417	130417	130417	130417	129384	129384	129384	129384
Adjusted R^2	0.258	0.258	0.258	0.258	0.209	0.209	0.209	0.209

Notes: Columns 1 and 5 report results of equation 4 excluding videos released day of interview itself and day after, columns 2 and 6 report results of equation 4. Models 3 (7) and 4 (8) correspond to columns 1 (5) and 2 (6) but using a binary measure of videos releasing. Data on outcome (ISIS approval) available from 2015 to 2018 included. Outcome variable standardized in range [0,100]. Data on outcome (ISIS respects traditions) available from 2016 to 2018 included. Outcome variable standardized in range [0,100]. Videos are available from wave 25(2014) to 42(2018). Baseline controls include age, gender, education and ethnic group. All models include district*time(wave) fixed effects. Standard errors in parentheses; clustered at the district level.
$*p < 0.10$ $**p < 0.05$ $***p < 0.01$

Table 5: Within Wave: Heterogeneity at Individual Level

	ISIS Approval			
	(1)	(2)	(3)	(4)
Videos	-0.181*	-0.231**	-0.253**	-0.217**
	(0.0978)	(0.0984)	(0.100)	(0.0991)
Videos x Age	-0.00268			
	(0.00228)			
Videos x Male		-0.0689		
		(0.0995)		
Videos x Education			-0.0423	
			(0.0584)	
Videos x Pashtun				-0.169
				(0.109)
Observations	130417	130417	130417	130417
Adjusted R	0.258	0.258	0.258	0.258

Notes: Table displays results for equation 5 including different types of heterogeneous effects at the individual level. Column 1 shows interaction with interviewee age, column 2 interaction with gender, column 3 interaction with education binary and column 4 interaction with pashtun indicator. Data on outcome (ISIS approval) available from 2015 to 2018 included. Outcome variable standardized in range [0,100]. Videos are available from wave 25(2014) to 42(2018). Baseline controls include age, gender, education and ethnic group. All models include district*time(wave) fixed effects. Standard errors in parentheses; clustered at the district level.

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

Table 6: Within Wave: Heterogeneity at District Level

	ISIS Approval				
	(1)	(2)	(3)	(4)	(5)
Videos	-0.445***	-0.410***	-0.251***	-0.579***	-0.629***
	(0.115)	(0.112)	(0.0960)	(0.163)	(0.176)
Videos × Close City	0.344***				
	(0.132)				
Videos × Urbanization		0.306**			
		(0.128)			
Videos × Opium			-1.391		
			(1.757)		
Videos × Fractionalization				0.739**	
				(0.319)	
Videos × Polarization					0.593**
					(0.247)
Observations	130417	129505	123713	130417	130417
Adjusted R^2	0.258	0.258	0.255	0.258	0.258

Notes: Table displays results for equation 5 including different types of heterogeneous effects at the district level. Column 1 shows interaction with proximity to cities, column 2 with urbanization level in district, column 3 with economic link to opium and columns 4 and 5 with a measure of ethnic fractionalization and polarization of district, respectively. Data on outcome (ISIS approval) available from 2015 to 2018 included. Outcome variable standardized in range [0,100]. Videos are available from wave 25(2014) to 42(2018). Baseline controls include age, gender, education and ethnic group. All models include district*time(wave) fixed effects. Standard errors in parentheses; clustered at the district level.
$*p < 0.10$ $**p < 0.05$ $***p < 0.01$

A Detailed Data Documentation

Table A.1: Variables description

Variable	**Content**	**Categories/Scale**	**Source**
Dependent variables			
ISIS arrival approved	Answer to question: “Do you think the arrival of Da’esh would be a good thing or a bad thing for Afghanistan?”	Possible answers: very bad, bad, neither good nor bad, good and very good. Normalized in interval [0, 100]	ANQAR survey
ISIS respects traditions	Answer to question: “Does Da’esh respect the religion and traditions of Afghans?”	Possible answers: completely respects, somewhat respects, does not respect very much and does not respect at all. Normalized in interval [0, 100]	ANQAR survey
Independent variables			
Local propaganda	Measured by the presence of daesh activity (black flags, night letters, publications and radio broadcasts) between waves 27 and 38 included	[0, 4]	Intel database
Videos	All videos released by ISIS in time-span 2014-2018	count	Intel database
Popular videos	Number of propaganda videos with >= 10 entry results in Google or Factiva search	count	Wilson report; Factiva database; own online search
Radio	Nangarhar radio signal weighted by population in settlements reached by signal itself	[0, 10]	Radio signal: US military, Afghan settlements: PIX
3G	Share of district population (2015 values) reached by 3G signal	[0, 100]	Collins Bartholomew (2021)
GSM	Share of district population (2015 values) reached by GSM signal	[0, 100]	Collins Bartholomew (2021)

Table A.2: Descriptive Statistics: Videos' language

Language	**Videos**	**% Videos**
Videos		
Arabic	3017	90.46
English	68	2.04
Pashto	27	0.81
Other	223	6.69
Subtotal	**3335**	**100**
Stills		
Arabic	2605	81.03
English	147	4.57
Pashto	164	5.10
Other	299	9.30
Subtotal	**3215**	**100**
Total	6550	

Notes: The analysis takes into account videos released between waves 25 and 33, included.

Table A.3: Descriptive Statistics: Videos' location

Language	**Videos**	**% Videos**
Videos		
Afghanistan	35	1.05
Iraq	1345	40.33
Syria	1458	43.72
Other	497	14.90
Subtotal	**3335**	**100**
Stills		
Afghanistan	240	7.47
Iraq	189	5.88
Syria	11	0.34
Other	2775	86.31
Subtotal	**3215**	**100**
Total	6550	

Notes: The analysis takes into account videos released between waves 25 and 33, included.

Figure A.1: Time-series: videos by categories

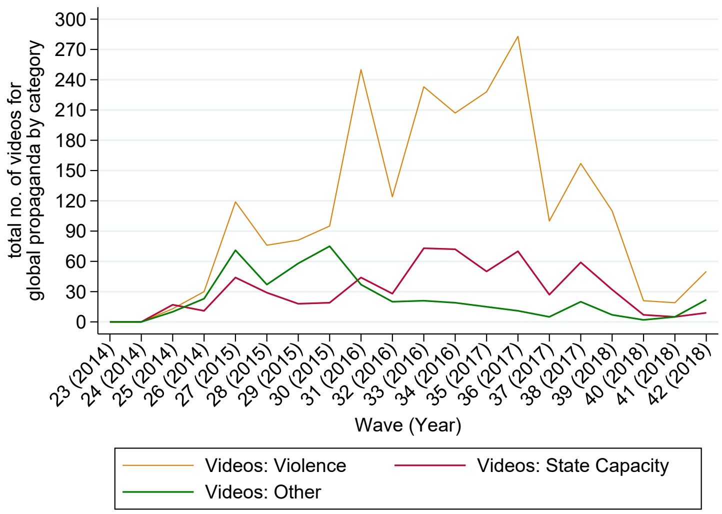
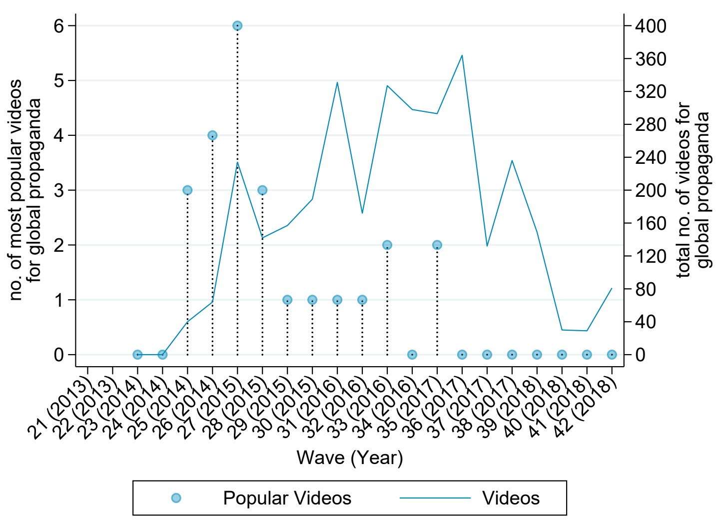


Figure A.2: Time-series: Intel videos and Popular videos



Notes: Information on the total number of videos comes from Intel. We considered popular videos those events highly present in medias. We exclude (videos on) events that happened in Afghanistan.

B Overall results

Table B.1: Local propaganda and ISIS approval
Remaining variables of Daesh activity

	ISIS Approval				ISIS Respects Traditions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Recruiting	3.537***				1.867**			
	(0.693)				(0.856)			
Supporters		3.720***				2.838***		
		(0.619)				(0.628)		
Show of Force			4.153***				3.194***	
			(0.802)				(0.744)	
Conflict				2.045***				0.966*
				(0.535)				(0.569)
Observations	85086	84986	85086	85062	37536	37519	37532	37528
Adjusted R^2	0.152	0.152	0.152	0.150	0.153	0.153	0.153	0.152

Notes: Table reports results of equation 1. Data on outcome (ISIS approval) available from 2015 to 2018 included. Outcome variable standardized in range [0,100]. Data on outcome (ISIS respects traditions) available from 2016 to 2018 included. Outcome variable standardized in range [0,100]. Analysis is based on events that happened in Afghanistan. Baseline controls include age, gender, education level and ethnic group. All models include district and time(wave) fixed effects. Standard errors in parentheses; clustered at the district level.
$*p < 0.10$ $**p < 0.05$ $***p < 0.01$

Table B.2: Global Propaganda and ISIS Approval
2-months window

[*Panel A*: Videos]

	ISIS Approval			ISIS Respects Traditions		
	(1)	(2)	(3)	(4)	(5)	(6)
Videos x 3G	-0.000**	-0.000	-0.000***	-0.000***	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Videos	-0.002	0.030	-0.010	0.011	0.021	0.011
	(0.024)	(0.019)	(0.023)	(0.016)	(0.017)	(0.016)
Videos x Nightlight			0.000**			-0.000
			(0.000)			(0.000)
Observations	130461	75419	130461	129385	71287	129385
Adjusted R^2	0.126	0.078	0.126	0.116	0.111	0.116
Joint significance (p-value)	0.914	0.119	0.652	0.493	0.227	0.492

[*Panel B*: Popular Videos]

	ISIS Approval			ISIS Respects Traditions		
	(1)	(2)	(3)	(4)	(5)	(6)
Popular Videos x 3G	-0.008**	-0.010	-0.003	0.009*	0.019**	0.009
	(0.004)	(0.006)	(0.004)	(0.005)	(0.008)	(0.006)
Popular Videos	0.244	-1.387	1.485	-4.255***	-5.166***	-4.252***
	(1.047)	(1.084)	(1.038)	(0.501)	(0.809)	(0.491)
Popular Videos x Nightlight			-0.023***			-0.001
			(0.007)			(0.011)
Observations	58001	33901	58001	38261	21144	38261
Adjusted R^2	0.182	0.097	0.183	0.153	0.127	0.153
Joint significance (p-value)	0.821	0.197	0.153	0.000	0.000	0.000

Notes: Table reports results of equation 3. Columns 2 and 5 restrict sample for districts with some access to GSM. Data on outcome (ISIS approval) available from 2015 to 2018 included. Outcome variable standardized in range [0,100]. Data on outcome (ISIS respects traditions) available from 2016 to 2018 included. Outcome variable standardized in range [0,100]. 3G is a continuous variable indicating the share of population with mobile coverage (2015). Nighlight inidicates nightlight data per district (2011). Joint significance tests if Videos/Popular Videos (two months before) + Videos/Popular Videos (two months before) x 3G equal zero. Baseline controls include age, gender, education and ethnic group. All models include district and time(wave) fixed effects. Standard errors in parentheses; clustered at the district level.
$*p < 0.10 **p < 0.05 ***p < 0.01$

Table B.3: Within Wave: Impact on ISIS Approval

	ISIS Approval			
	(1)	(2)	(3)	(4)
Videos	-0.274***			
	(0.0943)			
Videos (religious)		-0.877		
		(1.438)		
Videos (violence)			-0.336***	
			(0.116)	
Videos (state capacity)				-0.0308
				(0.245)
Observations	130417	130417	130417	130417
Adjusted R^2	0.258	0.258	0.258	0.258

Notes: Column 1 reports results of equation 4 excluding videos released day of interview itself and day after, while the following models consider only videos of the respective categories. Data on outcome (ISIS approval) available from 2015 to 2018 included. Outcome variable standardized in range [0,100]. Baseline controls include age, gender, education and ethnic group. All models include district and time(wave) fixed effects. Standard errors in parentheses; clustered at the district level.
$*p < 0.10$ $**p < 0.05$ $***p < 0.01$

Online Appendix

Table OA.1: Variable Group: Combatant Support

Variables	Definition
rategy_military	District share (NRVA): Household joined military
occupation_military	District share (AF):D-5:main occupation is Military/ Police
Dschamiat_Territory_1996	Dummy 1 if district belonged Dschamiat Territory in 1996
Dschunbisch_Territory_1996	Dummy 1 if district belonged Dschunbisch Territory in 1996
Hizb_i_Wahclat_Territory_1996	Dummy 1 if district belonged Hizb_i_Wahclat Territory in 1996
taliban1996	Dummy 1 if district belonged Taliban Territory in 1996
agree_averageANA	District average (AF): Q-16: agree that ANA is honest and fair with the Afghan people/ helps improve the security
ANA_defeatantigov	District share (ANQAR):Q115:ANA capable(as it is/but needs resources) to defeat
agree_averageANP	District average (AF): Q-17: agree that ANP is honest and fair with the Afghan people/helps improve the security
fear_ANP	District share (AF):Q-33d: some fear/a lot of fear for encountering Afghan national police
crime_cause_Taliban	District share (AF):Q-28:Taliban is the biggest cause of crime in Afghanistan
talibanreturn_good	District share (ANQAR):Q178:good for the people if Taliban returned to power
improvesecurity_taliban	District share (ANQAR):Q6:taliban is leading the effort to improve security
insecurity_taliban	District share (ANQAR):Q8:taliban/al Qaeda/AGE most bring insecurity to your area
insurgents_security	District share (ANQAR):Q381insurgents do a lot/little to prevent killing
sympathy_opposition	District share (AF):Q-51:you have sympathy for these armed opposition groups
Terrorist_Recruitment	(SA) Counter-insurgency: insurgents are actively recruiting or have successfully recruited individuals
Reintegration	(SA)Counter-Insurgency:Confrmed formal or informal reintegration of insurgents.
insurgent_more1	District share (ANQAR):Q381&Q382:insurgents do more than int. forces for security
deaths_1blameAGE	District share (ANQAR):Q431:GE/OGE/Taliban/Al Qaida/Islamic Extremist 1st to blame
deaths_blameTaliban	District share (ANQAR):Q431-433:Taliban is to blame when Afghan civilians are killed
reconciliation_helps	District share (AF):Q-47:the Afghan Government's reconciliation efforts and nego
deaths_1blameprogov	District share (ANQAR):Q431-433:Gov is to blame when Afghan civilians are killed
improvesecurity_gov	District share (ANQAR):Q6:government is leading the effort to improve security
intforces_security	District share (ANQAR):Q382:Int.Forces do enough to prevent the killing or injur
improvesecurity_foreign	District share (ANQAR):Q6:the foreign force is leading the effort to improve security
intforces_opinion	District average (ANQAR): Q22:opinion of Int. Forces: 1 (very high) to 5 (very low)
Supporting_CF	(SA)Non-Combat Event: Events where Local Nationals carry out activities in favour of Friendly Force

Table OA.2: Variable Group: Political/Ideological Preferences

Variable	Definition
good_national	District share (AF):Q-38a: agree that National Government is doing a very good job/somewhat good job
good_provincial	District share (AF):Q-38b: agree that Provincial government is doing a very good job/somewhat good job
disgov_overall_well	District average (ANQAR):Q195:District Governor do its job Overall well
gov_overall_well	District share (ANQAR):Q195:District Governor do its job Overall well
provgov_overall_well	District average (ANQAR): Q202:Provincial Governor do its job Overall well
gov_care_needs	District average(ANQAR): Q282a:Government cares about needs: does not care(1)
confidence_ministers	District share (AF):Q-37g:have confidence for Government Ministers and their jobs
gov_wrong_direction	District share (ANQAR):Q181:the Government is going in the wrong direction
disgov_improve	District share (ANQAR):Q201:the current district government will improve your quality of life
right_direction	District share (AF):Q-1 believe that things in Afghanistan today are going in the right direction
confidence_ShurasJirgas	District share (AF):Q-37f:have confidence for Community Shuras/ Jirgas and their jobs
confidence_parliment	District share (AF):Q-37k:have confidence for Parliment and their jobs
confidence_media	District share (AF):Q-37i:have confidence for Newspapers, print media , radio, Tv
confidence_InternationalNGO	District share (AF):Q-37h:have confidence for International NGOs and their jobs
confidence_nationalNGO	District share (AF):Q-37j:have confidence for National NGOs and their jobs
onlyboys_atschool	District share (ANQAR):Q307-308:only 6-14 years old boys in your household going to school or madrassa
madrassa	District average (NRVA):Share of hh member with madrassa attendance
politic_men	District share (AF):Q-70: agree that political leadership positions should be mostly for men
women_work_outside	District share (AF):Q-66:Agree that Women should be allowed to work outside
marriage_age	District average (NRVA):Average age of first marriage at Household level
income_female	District share (AF):D-19:female members of the family contribute to this household

Table OA.3: Variable Group: Security

Variable	Definition
AQ_presence	al-Qaeda presence
anybase	Dummy 1 if any military base is in the district
time_base	3D travel time to a military base
Cache_FC	(SA) Friendly action: supplies are hidden or otherwise concealed and are not readily available. (Cache Found / Cleared)
Close_Air	(SA) Friendly Action:fixed wing aircraft, delivers effects against an enemy force target
IED_Explosion	(SA) Explosive hazard: An IED event that results in a partial or complete functioning of an IED
IED_FC	(SA) Explosive hazard: the IED is removed from the fight before it can be used as intended
Insider_Attack	(SA) Friendly fire: host nation security forces opening fire on another host nation security forces is likely an insider attack
Terrorist_TP	(SA) Counter-insurgency:Insurgents are reported to have developed new or modified existing Techniques Tactics and Procedures
Sectarian_Violence	(SA)Non-Combat Event:Violence inspired by sectarianism
Tribal_Feud	(SA)Non-Combat Event: Events where violent or non-violent disputes have occurred between local tribes.
Demonstration	(SA) Non-Combat Event:Events where violent or non-violent protests are carried out by the local population
DirectFire	(SA) direct fire (e.g. small arms fire, sniper, drive-byshooting, deliberate aiming of a rocket)
IndirectFire	(SA) indirect fire(e.g. artillery, mortar and rocket)
brd_total_pre2001	Total sum of battle-related deaths before 2001, source: UCDP GED
best_est	Continuous number of battle-related deaths, source: UCDP GED
affected_violence	District share (NRVA): Affected by insecurity or violence or theft
violence_family	District share (AF):Q-23:you or your family has been a victim of violence
education_unsafe	District share (ANQAR):Q287:children are unsafe (very/little) when going to school
mantaqa_insecurity	District share (ANQAR):Q2:the security situation in your mantaqa is bad
districtroads_unsafe	District share (ANQAR):Q5:feel unsafe using the roads in your district
fear_demonstration	District share (AF):Q-33b: some fear/a lot of fear for participating in a peaceful demonstration
AGE_influence	District share (ANQAR):Q176:AGE has more influence in mantaqa than Government

Table OA.4: Variable Group: Corruption and Crime

Variables	Definition
Heroin_Processing_Lab	Dummy 1 if at least one heroin processing lab is in the district
eradication	eradication (ha), verified 2007-2015, est 2006, missing 2008, source UNODC
Major_Opium_Market	Dummy 1 if at least one Major Opium Market is in the district
Morphine_Lab	Dummy 1 if at least one Morphine lab is in the district
cultivation	Cultivation of opium in hectares, source UNODC
Sub_Opium_Market	Dummy 1 if at least one Sub Opium Market is in the district
anyopium	District share (NRVA): Any (1st,2nd,3rd) important crop is opium
affected_opium	District share (NRVA): Affected by opium eradication or grew opium last season but not this season
total_markets	Sum of all Opium Markets
criminal_often	District average (ANQAR): Q424:frequency of committed crimes in community: never
Finance	(SA)Criminal Event:Activities tied to funding of illegal events or terrorist activities, such as money laundering.
Illegal_Checkpoint	(SA)Criminal Event: Reporting of checkpoints that have not been approved by the GIRoA or established by ANDSF or ISAF/RS.
ANA_improperactions	District share (ANQAR):Q102:National Army improper actions
ANP_improperactions	District share (ANQAR):Q35:ANP improper actions
corruption_daily	District average (AF): Q-29a:corruption is a major problem in your daily life
corruption_neighborhood	District average (AF): Q-29b:corruption is a major problem in your neighborhood
corruption_local	District average (AF): Q-29c:corruption is a major problem in your local authority
corruption_provincial	District average (AF): Q-29d:corruption is a major problem in your provincial gov
corruption_Afghanistan	District average (AF): Q-29e:corruption is a major problem in Afghanistan
corruption_affectlife	District share (ANQAR):Q349:corruption in the Government affects daily life
gov_corruption_serious	District share (ANQAR):Q217:agree (strongly/somewhat) that corruption is serious
crime_cause_unemployment	District share (AF):Q-28:Unemploymentis the biggest cause of crime in Afghanistan
crime_cause_corruption	District share (AF):Q-28:Corruption is the biggest cause of crime in Afghanistan

Table OA.5: Variable Group: Institutions

Variable	Definition
occupation_govt	District share (AF):D-5:main occupation is Government Office
dispute_statecourt	District share (ANQAR):Q312:would take legal dispute to an Afghanistan state court
agree_courts_equity	District average (AF): Q-59:share of responses agree with the equity of State Court
agree_courts_efficiency	District average (AF): Q-59:share of responses agree with the efficiency of courts
agree_JirgasShuras_efficiency	District average (AF): Q-60:share of responses agree with the efficiency of jirgas and shuras
agree_JirgasShuras_equity	District average (AF): Q-60:share of responses agree with the equity of jirgas and shuras
dispute_shura	District share (ANQAR):Q312:would take legal dispute to a local Shura/Jirga court
anyschool	District share (NRVA,shuras): Any type of school present in the community
highedu	District average (NRVA):Share of household member with higher education attended
edu_never	District share (AF):D-10: never went to school
dist_anyschool	District average (NRVA,shuras): Mean distance to all schools in km
satisfaction_education	District share (ANQAR): Q261:satisfaction with Education in area:very very dissatisfied (1) to very satisfied (5)
health_facility	District share (NRVA,shuras): Any health facility in/near community: <=2h (any transportation type)
public_clinic	District share (NRVA,shuras): District share (NRVA,shuras): Minimal time to public clinic(by different transportation type)
district_hospital	District share (NRVA,shuras): District share (NRVA,shuras): any hospital in/near community: <=2h (any transportation type)
healthcare_badquality	District share (ANQAR):Q317:quality of healthcare available in area is none/very
satisfaction_healthcare	District share (ANQAR): Q259:satisfaction with healthcare in area:very very dissatisfied (1) to very satisfied (5)
Disease	(SA) Non-Combat Event:Events where any breakout of illness or disease is reported.
ANP_protect	District share (ANQAR):Q25(2012):Police somewhat and very capable to protect mantaqa
police_often	District share (ANQAR):Q27:Presence of police in mantaqa >= once a week
borderpolice_overall	District share (ANQAR):Q84:Border Police effective in securing overall borders
ANA_seen_often	District share (ANQAR):Q116(2012):ANA presence in mantaga >= 2-3 times a month

Table OA.6: Variable Group: Development Aid

Variable	Definition
school_aid	District share (NRVA,shuras): Community project: School construction/rehabilitation created
literacytraining_aid	District share (NRVA,shuras):Community project: Literacy/vocational training created
project_healthcare	District share (AF):Q-11h:Healthcare (primary health center, regular visits of doctors, etc.) in your area in the last 12 months
healthfacility_aid	District share (NRVA,shuras): Community project: Health facility construction/rehabilitation created
shelter_aid	District share (NRVA,shuras):Community project: Shelter project for returnees created
drainage_aid	District share (NRVA,shuras):Community project: Drainage structures (bridges/culverts/washes) created
electricity_aid	District share (NRVA,shuras): Community project: Electricity - micro-hydro, diesel generator created
floodwall_aid	District share (NRVA,shuras): Community project: Flood/river protection wall created
microfinance_aid	District share (NRVA,shuras): Community project: Micro-finance project created
strategy_project	District share (NRVA): Household participated in any cash/food-for-work or income-generation project
incomegeneration_aid	District share (NRVA,shuras): Community project: Income generation project for women created
project_agriculture	District share (AF):Q-11j:Reconstruction/programs in agriculture in your area in the last 12 months
irrigation_aid	District share (NRVA,shuras):Community project: Irrigation infrastructure improved/constructed
reforestation_aid	District share (NRVA,shuras): Community project:: Reforestation/tree nurseries/orchard/fruit tree
road_aid	District share (NRVA,shuras): Community project: Road/bridge construction/rehabilitation created
watersupply_aid	District share (NRVA,shuras): Community project:Water supply/construction of wells with hand pumps created
project_industry	District share(AF):Q-11k:Reconstruction/programs in industry in your area in the last 12 months
project_mosques	District share(AF):Q-11l: Building new mosques in your area in the last 12 months
strategy_relief	District share (NRVA): Household worked on relief programmes
strategy_community	District share (NRVA):Household received help from others in the community
anyproject_aid	District share (NRVA,shuras): Community project: Any programme created
project_diversity_aid	District average (NRVA,shuras): Community project:total number of the infrastucture or programme created
project_any	District share (AF):Q-11:Any project in your area in the last 12 months
project_diversity	District average (AF): Q-11:Diversity of project in your area in the last 12 months

Table OA.7: Variable Group: Geography

Variable	Definition
pashtuns	share of pashtun ethnic group, source:NATO
tajiks	share of tajik ethnic group, source:NATO
hazaras	share of hazara ethnic group, source:NATO
uzbeks	share of uzbek ethnic group, source:NATO
turkmen	share of turkman ethnic group, source:NATO
arabs	share of arab ethnic group, source:NATO
nuristanis	share of nuristanis ethnic group, source:NATO
balochis	share of balochi ethnic group, source:NATO
ethnic_frac	ethnic fractionalization
No_ethnic_greg	Number of Ethnic groups, source: NATO
ethnic_polar	ethnic_polarization
pop	Population: ipolated data from 2000 till 2015
border	Dummy 1 if district is a border district
bordercrossing	Dummy 1 if there is an unofficial border crossing
ruggedness	Raster average: Nunn & Puga ruggedness index
urban	District share (NRVA): Urban
time_3d_anycity	Minumum 3D Travel time to any city (Kunduz, Kandahar, Hirat, Mazari, Jalalabad)
time_3d_Kabul	3D Travel time to Kabul
suitability_rw_opium	Population weighted opium suitability
suitability_rw_wheat	Wheat suitability index (values) for current cultivated land for intermediate input, population weighted
vhi	Vegetation Health Index: low values represent drought conditions, Source: FAO
Natural_Disaster	(SA)Non-Combat Event: Natural Disaster

Table OA.8: Variable Group: Economic Conditions

Variables	Defination
internet	District share (NRVA): any HH member have used internet
mobile	District share (NRVA): any HH member mobile phone
noelectric	District share (NRVA): Household has no electricity (at all)
itemvalue	District average(NRVA): Current item value of household's assets
satisfaction_road	District share (ANQAR):Q257: satisfaction with Roads in area:very dissatisfied (1) to very satisfied (5)
satisfaction_water	District share (ANQAR):Q258: satisfaction with Water in area:very dissatisfied (1) to very satisfied (5)
satisfaction_electricity	District share (ANQAR):Q260: satisfaction with Electricty in area:very very dissatisfied (1) to very satisfied (5)
satisfied_life	District share (ANQAR):Q280:satisfied with your current quality of your life
satisfaction_average	District average (ANQAR): Q257-262average scale for satisfaction with the provision of 6 services
rate_economic	District average (NRVA): Household's economic situation (the higher, the better)
problem_economic	District share (ANQAR):Q223:individual economic conditions as 1st mentioned problem
foodmarket_time	District average (NRVA,shuras): Minimal time to food market (any transportation)
watersource_time	District average(NRVA): Walking time to water source (mins.)
road_distance	District average (NRVA,shuras): Km Distance to nearest drivable road
ma_nightlight_3d	Market Access using nightlight as population and total_length as distance
ma_totmarkets_3d	Market Access using total_markets as population and slength as distance
nightlight	Nightlight data per district
satisfaction_employment	District share (ANQAR): Q262: satisfaction with Jobs/Employment in area:very dissatisfied (1) to very satisfied (5)
income	District average (AF): D-18b: categories that best represents average total family
hh_unemployed	District share (ANQAR):Q303:number of hh members searching for work and are not employed
anyselfemployed	District share (NRVA): Any household member is self-employed
unemployment_first	District share (AF):Q-4a:the biggest problem in your local area is unemployment
unemployment_second	District share (AF):Q-4b:the next biggest problem in your local area is unemployment
shareagri	District average (NRVA): Share of hh members who work in agriculture/livestock
occupation_agriculture	District share (AF):D-5:main occupation is Farmer (own land / tenant farmer)
sharework	District average (NRVA): Share of hoursehold member work for pay/profit/family gain
Displaced_Persons	(SA)Economic Event:Event where persons are reported to leave their homes or places of habitual residences