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Transnational Terrorism and the Internet

Quy-Toan Do
Nicolas Gomez-Parra
Bob Rijkers

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Abstract

Does the internet enable the recruitment of transnational terrorists? Using geo-referenced population census data and personnel records from the Islamic State in Iraq and the Levant—a highly tech-savvy terrorist organization—this paper shows that internet access has facilitated the organization's recruitment of foreign fighters from Tunisia. The positive association between internet access and Daesh recruitment is robust to controlling for a large set of observable and unobservable confounders as well as instrumenting internet access rates with the incidence of lightning strikes.

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1 Introduction

The internet has had a transformative impact on society, promoted trade, and generated growth (Freund and Weinhold, 2004; Litan and Rivlin, 2001). Yet, it has also enabled various forms of crime (Bhuller et al., 2013; Müller and Schwarz, 2021), reduced confidence in government in most countries (Miner, 2015; Guriev et al., 2020), and long raised concerns about its use by violent extremists (Gartenstein-Ross, 2017; Conway, 2017). The Islamic State in Iraq and the Levant (ISIL, also known as Daesh) has been the epitome of tech-savvy terrorism and has attracted an estimated 30,000 foreign recruits from 89 countries to Syria and Iraq (Benmelech and Klor, 2018), about 6,000 of whom came from Tunisia (Berger and Morgan, 2015; Soufan Center, 2015; Benmelech and Klor, 2018), the largest country contingent in per capita terms. While Daesh's reliance on social media – to spread propaganda, secure financing, plan attacks, proselytize, and recruit– is well-documented (FATF, 2015; Greenberg, 2016; Bloom et al., 2017; Conway et al., 2019; Mitts et al., forthcoming), the internet can also hamper its transnational terrorist recruitment efforts; it can enhance the efficiency of law enforcement or of repression by the state (Rød and Weidmann, 2015; Baum and Potter, 2019; Gohdes, 2020; Mastrobuoni, 2020), positively reshape public views of government (Gunitsky, 2015; King et al., 2017; Qin et al., 2017; Guriev and Treisman, 2019), and increase the opportunity cost of joining the terror group by improving labor market prospects (Autor, 2001; Hjort and Poulsen, 2019). The overall extent to which the internet has enabled the international recruitment of jihadists is, therefore, theoretically ambiguous.

This paper addresses this question empirically by using a unique dataset on Tunisians who joined Daesh in Syria and Iraq between early September 2013 and late 2014. The data contain information on recruits' ages, education levels, and delegations (district) of residence before traveling abroad, allowing us to exploit variation in enrollment both between and *within* geographical areas, and between age and education groups.[1] These granular data are matched with equally granular socio-economic information obtained from the 2014 Tunisia Census of Population and Housing. Thus, for each delegation-education-age cell, we are able to associate

[1] Tunisia's smallest administrative units are the communes, which form the country's 264 delegations, which in turn aggregate into 24 governorates.

the number of Daesh recruits with both the internet access rate as well as other socio-economic variables that may promote radicalization such as unemployment and marital status.

Our main finding is that internet access does predict jihadist recruitment. This result is robust to controlling for a large set of potential confounders, including age and education group dummy variables, and delegation fixed effects. While these fixed-effect estimations account for a large set of unobservables that have impeded the causal interpretation of earlier observational studies of the drivers of terrorism (see discussions in Krueger and Malečková, 2003; Abadie, 2006; Krueger and Laitin, 2008), we further provide two-stage least squares estimates using the incidence of lightning strikes as instrument for internet access rates (Manacorda and Tesei, 2020; Guriev et al., 2020). The IV estimates are significant and larger than their OLS analogs. We check the robustness of our findings to various alternative specifications, sample restrictions, and standard error corrections that account for spatial correlation. Our most conservative estimate implies that a one percent increase in internet coverage would result in an additional 2 recruits showing up in our sample or roughly 25 individuals overall. These numbers correspond to a .56 elasticity of recruitment with respect to internet access rates.

This paper builds on and aims to contribute to two strands of literature that as yet have had little overlap. Our main finding relates to the emerging literature on the political implications and impacts on crime of internet expansion (see Zhuravskaya et al., 2020, for a review). By specifically looking at radicalization into violent extremism, our results also contribute to the literature on the drivers of terrorism in general (Li and Schaub, 2004; Gassebner and Luechinger, 2011; Gaibulloev and Sandler, 2019; Krueger and Malečková, 2003), and transnational terrorism in particular (Bandyopadhyay and Younas, 2011; Enders and Hoover, 2012; Benmelech and Klor, 2018; Brockmeyer et al., forthcoming; Hegghammer, 2013). This paper thus adds to the nascent literature on quantitative analyses of the relationship between the internet and violent extremism (Warren, 2015; Bail et al., 2018; Mitts, 2019; Mitts et al., forthcoming).

The remainder of the paper is organized as follows. The next section presents our empirical strategy. The data are described in section 3. In section 4, we present and discuss our results; section 5 summarizes our results and draws conclusions.

2 Empirical strategy

Our main empirical specification identifies the conditional correlation between radicalization into violent extremism and internet access at the delegation-education-age level (see section 3 for a discussion of how the data are constructed). The dependent variable is the inverse hyperbolic sine (ihs) transformation of R_{dea}, the number of recruits in district d who joined Daesh in Syria and Iraq that have education level e (primary or below, secondary, and tertiary and above) and belong to age group a (where individuals have been grouped in 5-year age categories).[2] We estimate

$$asinh(R_{dea}) = \alpha Internet_{dea} + \beta Population_{dea} + \gamma X_{dea} + \varepsilon_{dea} \quad (1)$$

where $Internet_{dea}$ is the share of men in delegation d with education level e in age group a who have access to the internet, $Population_{dea}$ is the (log of the) total number of men in a delegation-age-education cell $\{d, e, a\}$, and X_{dea} is a vector of controls. All these independent variables are measured in 2014, the year the data on Daesh recruits are believed to be from (Dodwell et al., 2016a). The coefficient of interest, α, measures the impact of internet access on the propensity to join the terrorist organization.

Theoretically, the sign of α is ambiguous. On the one hand, the internet enables Daesh to spread propaganda and thus increase its "labor supply" (Bloom et al., 2017). It also reduces transaction costs associated with recruiting, similar to the effect internet has on licit recruitment efforts by regular firms (Autor, 2001). On the other hand, the internet facilitates law enforcement, repression of dissent (Greenberg, 2016; Conway et al., 2019; Gohdes, 2020) and can reduce grievances against the government by positively (re-)shaping citizens' views (Gunitsky, 2015; Rød and Weidmann, 2015; King et al., 2017; Qin et al., 2017; Guriev and Treisman, 2019). Which channel dominates is, therefore, an empirical question; the reduced-form impact α reflects the net effect of all these potential mechanisms.

[2] The ihs transformation approximates the natural logarithm of the variable for large values, while retaining 0 values (see, e.g., Burbidge et al., 1988; Bellemare and Wichman, 2020), and helps reduce the skewness of the dependent variable. Appendix Table A3 produces regression results with alternative transformations of the Daesh recruit count variable, including the linear R_{dea}, $\log(1 + R_{dea})$, and the dummy variable $\mathbb{1}\{R_{dea} > 0\}$. Given that most cells do not have any recruits, the log transformation $\log R_{dea}$ is not an appropriate alternative.

Ordinary Least Squares (OLS) estimates of this parameter, however, will potentially be biased. To alleviate potential endogeneity concerns, we use two different empirical strategies.

Fixed effects A first approach consists of controlling for delegation, education, and age group fixed effects. Namely, we write error term ε_{dea} as

$$\varepsilon_{dea} = \theta_d + \theta_e + \theta_a + \zeta_{dea}. \tag{2}$$

Fixed-effect estimations account for observable and non-observable delegation characteristics; our identification therefore leverages differences between individuals whose age and education differ but who live in the same delegation. This strategy accounts for common unobserved delegation characteristics such as delegation-level income, local inequality, availability and quality of public services, local government repression, and history.

Our fixed-effect estimates might nonetheless be biased if some unobserved cell characteristics were correlated with both internet access and propensity to join Daesh. Similarly, it may fail to address reverse causality: individuals who would want to enlist might actively seek an internet connection to do so. However, given that the total number of Daesh recruits is very small, 0.046 percent of the total population, reverse causality is unlikely to be of first order relevance as it would explain a negligible portion of internet access.

Instrumental variables To address the potential biases, we use an instrumental variable strategy, which consists of estimating (1) using two-stage least squares (2SLS), with a first stage of the form

$$Internet_{dea} = \gamma Z_d + X_{dea} \cdot \eta + \nu_{dea} \tag{3}$$

where Z_d is a variable that varies geographically only and affects internet access but is excluded from the second stage.

To that end, we follow Manacorda and Tesei (2020), Guriev et al. (2020), and Andersen et al. (2012) and construct instrumental variable Z_d, which measures the incidence of lightning strikes on delegation d as proxied by flash density, i.e. the average number of ground flashes per square kilometer per year between 1995 and 2010. The rationale behind the first stage is that lightning strikes increase the user cost of IT related infrastructure because they create voltage surges and dips (Andersen et al., 2011, 2012); accordingly, we expect a negative first-stage coefficient.

Our exclusion restriction, therefore, postulates that lightning strikes affect radicalization only through their impact on internet access. However, as discussed by Manacorda and Tesei (2020), lightning strikes might be correlated with other climatic or topographical characteristics like rainfall, which in turn might affect economic development. Since the instrument varies only at the delegation level, controlling for delegation fixed effects is no longer feasible. We nonetheless include in the vector of control variables X_{dea} a measure of delegation d's income as proxied by (log) nighttime lights, its (log) area, and the (log) average monthly amount of rain that fell there.

Addressing spatial correlation The instrumental variable strategy makes salient that deployment of the internet, a network technology, is likely to be spatially correlated. Thus, for both error terms ε_{dea} (or ζ_{dea} for the fixed-effect estimations) and ν_{dea}, we allow for spatial correlation. We first allow ε_{dea} and $\varepsilon_{de'a'}$ to be correlated, by clustering standard errors at the delegation level, but given the potential spatial dependence in internet access and its instrumental variable, our preferred specifications use the procedure from Conley (1999) to accommodate spatial correlation.

3 Data

To estimate equation (1) and its variants, we combine a dataset on Daesh foreign personnel that contains information on Tunisian recruits with socio-economic and other data on the geographic areas those recruits are coming from.

Daesh foreign recruits Our main source of data comes from Daesh administrative records on its foreign fighters. The dataset, believed to have been leaked by a defector, covers 3965 male foreign recruits, which constitutes an estimated 30 percent of foreign fighters who joined the organization from early 2013 through late 2014 (Dodwell et al., 2016a).[3]

[3] Dodwell et al. (2016a) checked the information in the database against U.S. Department of Defense intelligence records and found high levels of consistency. The data were used in earlier cross-country studies (Dodwell

The data have the advantage that recruits report not only their age and education but also where they resided before enrolling; of the 605 Tunisian recruits, we are able to map delegation of residence for 501, of whom 468 also have information on education and age. Our sample for the analysis thus consists of these 468 Daesh recruits.[4]

The average number of recruits per delegation is 1.9, but the average masks a highly skewed distribution (see Figure 1a): recruits come from 94 delegations only (out of 263), whereas Bizerte, the northernmost city in Africa, had 30, the highest number. The Tunis area was also a recruitment hotspot. Of the 468 Tunisian recruits in our database, 128 are from the governorates of Tunis and Bizerte. In general, recruitment rates are much higher in urban areas.

Detailed information on the socio-economic characteristics of recruits (including their age and education), allows us to construct a variable of recruitment that counts the number of Tunisian recruits who resided in delegation d, have education level e, and have reported to be a years old; we therefore created five-year age groups so that each cell (observation) in the dataset is characterized by the triplet $\{d, e, a\}$. Table 1 provides both cell-level and delegation-level summary statistics for our variables of interest. The number of recruits in a given cell ranges from 0 to 8.

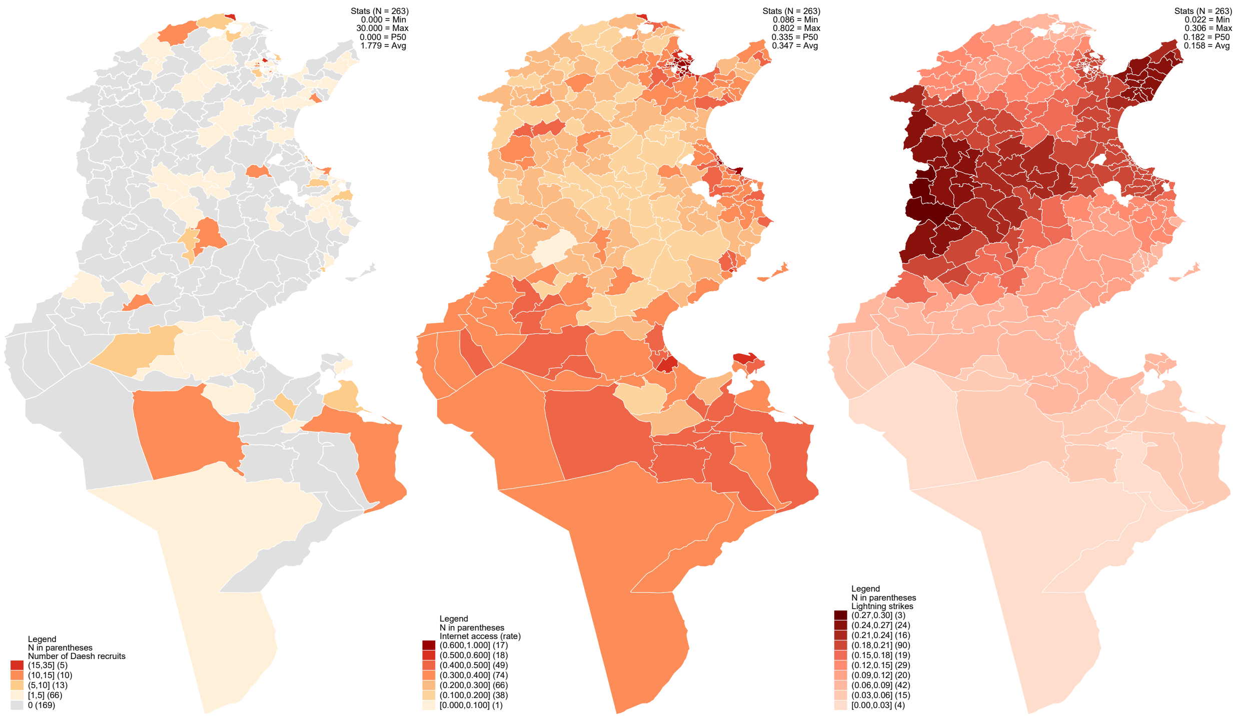
Socio-economic data The 2014 Tunisia Census of Population and Housing is the source of our main independent variables. The census collected information on demographics, educational attainment, marital status, unemployment, television and radio ownership, emigration, and

et al., 2016a,b; Jayakumar and Sumpter, 2019; Morris, 2020; Evans et al., 2020; Brockmeyer et al., forthcoming), but to the best of our knowledge they have not been used for country case studies.

[4] Using available information on Daesh recruit age, education, occupation before joining, marital status, previous experience with jihad, and self-reported knowledge of Islam, Appendix Table A2 presents tests examining whether there are systematic differences in the characteristics of fighters who were included in the analysis and those who are not. For each variable grouping, the F-test of joint significance of the difference in means between our sample and the data universe fails to reject that these are equal to zero. Our analysis sample thus does not appear to suffer from selection bias. In addition, Brockmeyer et al. (forthcoming) show that the larger database exhibits high correlation with alternative sources of information on Daesh foreign recruits; they look at country aggregates and conclude that the data are representative at the country level. We conduct a similar exercise and compare the reported delegations of last residence for observations in our dataset with the ones obtained by Zelin (2018) on 121 Tunisian recruits who died in Syria and Iraq. The correlation between our data on recruitment per delegation and Zelin's measure of deceased foreign fighters per delegation is 0.71. Our data thus appear to accurately represent the spatial distribution of Daesh recruitment in Tunisia.

Figure 1: Recruits, internet access, and lightning strikes in Tunisia

(a) Number of Daesh recruits (b) Internet access (rate) (c) Lightning strikes



Notes: Figure 1a maps the total number of Daesh recruits in each delegation. Figure 1b indicates internet access rates (as measured by the share of men that used the internet in the last 3 months) for each delegation. Figure 1c shows the intensity of lightning strikes for each delegation (as measured by the average yearly number of strikes per square kilometers over the period 1990-2010). Appendix Table A1 provides variable definitions.

Table 1: Descriptive statistics

	N	Mean	Std. Dev.	Min	Max
Panel A: Delegation-age-education {dea} level variables					
Internet access (rate)	7878	0.437	0.306	0.000	1.000
Married (rate)	7878	0.597	0.377	0.000	1.000
Number of Daesh recruits	7878	0.059	0.366	0.000	8.000
Population – in thousands	7878	0.520	0.579	0.001	5.237
Radio ownership (rate)	7878	0.535	0.165	0.000	1.000
TV ownership (rate)	7878	0.953	0.038	0.000	1.000
Unemployment (rate)	7878	0.088	0.104	0.000	1.000
Panel B: Delegation d level variables					
Main					
Area – in thousands	263	0.587	1.855	0.002	26.526
Internet access (rate)	263	0.347	0.141	0.086	0.802
Married (rate)	263	0.566	0.034	0.380	0.639
Mountains (share)	263	0.179	0.288	0.000	1.000
Number of Daesh recruits	263	1.779	4.355	0.000	30.000
Lightning strikes	263	0.158	0.064	0.022	0.306
Radio ownership (rate)	263	0.509	0.144	0.101	0.817
TV ownership (rate)	263	0.949	0.022	0.832	0.983
Unemployment (rate)	263	0.079	0.033	0.027	0.252
1995-2010 nighttime lights – in thousands	263	2.331	1.772	0.122	16.965
1995-2010 rainfall	263	33.657	15.494	5.401	83.211
2014 nighttime lights – in thousands	263	4.407	4.542	0.126	60.279
2014 rainfall	263	31.319	14.817	4.310	84.919
Other outcomes					
Convicted terrorists	263	0.487	1.223	0.000	11.000
Emigration (rate)	263	0.010	0.010	0.000	0.074
Islamist vote (share)	263	0.279	0.121	0.089	0.678
Jihadist lectures (dummy)	263	0.198	0.399	0.000	1.000
Protests and riots	263	4.719	22.714	0.000	346.0

Notes: Our analysis considers 263 delegations rather than 264 because Douz North and Douz Sud are combined into one reporting area. We only consider male population in our estimations where possible - data on elections and civil unrests are not disaggregated by gender. Variables expressed in thousands are multiplied by 1000 throughout our analyses. Variable definitions are available in Appendix Table A1.

internet access.[5] The average delegation has a 35 percent (male) internet access rate; the aggregate nation-wide rate is 39 percent because more densely populated urban areas tend to be more connected. Figure 1b shows how geographically heterogeneous internet access is; metropolitan areas closer to the coast have high access rates, while these tend to be low in the interior of Tunisia and in delegations abutting the Algerian border.

To match census data with our Daesh recruit data, we aggregate the census data to a level below the delegation, i.e. the cell level. Recall that a cell is characterized by the delegation d, education level e (primary or below, secondary, and tertiary and higher), and a five-year age group a (starting from at 15-19 through 60-64). We construct demographic, unemployment, and internet and media usage variables for each cell by taking the mean among men in that cell. Our data set thus consists of 7890 observations, but the population in 12 of the $\{d, e, a\}$ cells is equal to zero, so they are excluded them from the estimation sample, which eventually consists of 7878 cell-level observations. Definitions and sources of the variables used in our analyses are provided in Appendix Table A1 and summary statistics in Table 1.

Instrumental variables As an instrumental variable for internet access, we use the average lightning strike intensity per square km per year over the period 1995-2010 obtained from Manacorda and Tesei (2020). They use data collected by the U.S. National Aeronautics and Space Administration (NASA) and processed by the Global Hydrology Resource Center (GHRC). Figure 1c shows the spatial distribution of lightning strikes. The map shows a high degree of spatial correlation, underscoring the need to accommodate this feature in the econometric analysis. Lightning strikes are least prevalent in the south, which is covered by the Sahara desert, and most prevalent in the Chaambi mountains close to the Algerian border and in the Cape Bon peninsula located in the North East. A comparison of the spatial variations in lightning (Figure 1c) and in internet access (Figure 1b) points to a high correlation.

Other data We complement census data with delegation-level nighttime light data (Li et al., 2020) for the 1995-2014 period, which we use as a proxy for income. Information on

[5] We only consider metrics for the male population where possible, since the sample of recruits comprises men only. In practice, this distinction makes little difference to our results. The correlation between male internet access rate and overall internet access rate is $\rho = .94$.

elevation (mountains) comes from the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC, 2002). Rainfall data were obtained from the GPCC Global Precipitation Climatology Centre (Schneider et al., 2015). We also collected data on Tunisia's socio-political landscape, using legislative election data for 2014 from the national election authority (ISIE, 2015). Finally, alternative measures of violent extremism comprise information on political protests, riots, and political violence from the Armed Conflict Location & Event Data (ACLED) Project database (Raleigh et al., 2010) and Zelin (2020)'s data on the locations where extremist group Ansal al-Sharia Tunisia (AST) delivered jihadist religious lectures - a vehicle for the group's proselytization and recruitment activities. We also compiled data from the National List of Persons, Organizations and Entities Associated with Terrorist Crime curated by the anti-terrorism commission, which tracks all individuals indicted for terrorism as listed in the Official Gazette (CNLCT, 2021). It also lists their addresses, which allows us to georeference them.[6]

4 Results

Our main finding that internet access predicts recruitment is shown in Table 2. Columns 1-6 show progressively more stringent OLS estimation results. Column 1 documents a positive and statistically significant correlation between (the inverse hyperbolic sine of- henceforth ihs) the number of Daesh recruits and internet access rates, while normalizing by the population of each cell by controlling for the logarithm of the number of men in a particular delegation-education-age cell as enumerated in the census. Standard errors are clustered at the delegation level. Recognizing that the nature of internet access might lead error terms in (1) to be spatially correlated, the specification in column 1 is replicated in column 2 but following Conley (1999) to account for spatial correlation of the error term with a 50-km buffer area. The results are very similar. Given the scope for spatial correlation in internet access, we henceforth adopt Conley (1999) standard error correction procedures.

This association between internet access and jihadist recruitment is robust to including addi-

[6] Note that the terrorist acts documented therein were committed between 2004 and 2018; the timespan the data cover is thus different from that covered by our data on Daesh recruitment

tional control variables. Column 3 shows that adding delegation-level controls such as income (proxied by nighttime light intensity and rainfall, both averaged over the years 1995-2010), and $\{dea\}$ cell-level controls including unemployment and marriage rates, education and age-category dummy variables, leads to a reduction in the coefficient on internet access. These control variables not only explain Daesh recruitment but are also correlated with internet access. Column 4 adds a control for the Islamist vote share in the 2014 legislative elections (ISIE, 2015) as a proxy for political preferences for Islamism; doing so hardly affects the coefficient on internet access. Next, in column 5, we add proxies for extremism notably the occurence Ansar-Al-Sharia-sponsored jihadist lectures (Zelin, 2020), the number of convicted domestic terrorists (CNLCT, 2021), and the incidence of violent protests and riots (Raleigh et al., 2010). These variables could themselves be influenced by internet penetration; the estimated coefficient of interest thus captures the effect of internet access on Daesh recruitment above and beyond the internet's independent influence on these other forms of radicalization. Delegations where Ansar-Al-Sharia-sponsored jihadist lectures took place are more likely to produce Daesh recruits and the slight reduction in the coefficient for internet access is suggestive that internet might actually have played a role in the decision to locate these lectures.[7] Finally, to capture *all* sources of latent delegation-level heterogeneity, both observable and unobservable, we add delegation fixed effects in column 6, which presents our preferred OLS specification. While less precisely estimated, the coefficient for the internet remains positive and statistically significant at the 5 percent level. In short OLS estimations yield a robust correlation between internet access and the extent of Daesh foreign fighter recruitment.

As discussed in Section 2, our fixed-effects estimation in Column 6 accounts for both observable and non-observable delegation-level characteristics. As such, delegation-level variables such as income, civil liberties, availability and quality of public goods, government repression, etc. are accounted for in the delegation fixed-effect variable. However, since we cannot rule out latent heterogeneity, fixed-effect estimations might still be biased. We therefore estimate the relationship using 2SLS. We instrument the internet variable using lightning strike counts (Manacorda and Tesei, 2020; Guriev et al., 2020), which measure the average number of lightning strikes

[7] In separate analyses not shown here, we however do not find any significant correlation between internet access and the occurrence of jihadist lectures.

Table 2: Internet and transnational jihadist recruitment

Dependent variable	Number of Daesh recruits (inverse hyperbolic sine)							
	OLS						2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS and 2SLS second stage								
Internet access (rate)	0.105	0.105	0.074	0.075	0.060	0.072	0.318	0.557
	(0.017)	(0.016)	(0.025)	(0.025)	(0.025)	(0.028)	(0.159)	(0.214)
Population (log)	0.026	0.026	0.013	0.013	0.007	-0.002	0.002	-0.014
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.008)	(0.010)
Unemployment (percentage)			0.012	0.012	0.002	0.014	0.056	0.096
			(0.039)	(0.039)	(0.038)	(0.037)	(0.053)	(0.060)
Married (percentage)			-0.033	-0.032	-0.012	0.027	0.001	0.064
			(0.040)	(0.041)	(0.042)	(0.042)	(0.048)	(0.057)
Delegation area (log)			-0.009	-0.009	-0.003		-0.002	0.009
			(0.003)	(0.003)	(0.002)		(0.005)	(0.006)
1995-2010 nighttime lights (log)			-0.003	-0.003	-0.006		-0.002	-0.001
			(0.005)	(0.005)	(0.005)		(0.005)	(0.006)
1995-2010 rainfall (log)			-0.009	-0.010	-0.009		0.005	0.013
			(0.006)	(0.007)	(0.007)		(0.012)	(0.014)
Islamist vote (share)				-0.005	-0.025			-0.081
				(0.026)	(0.026)			(0.036)
Jihadist lectures (dummy)					0.067			0.055
					(0.010)			(0.010)
Convicted terrorists					0.010			0.011
					(0.004)			(0.004)
Protests and riots					0.000			0.000
					(0.000)			(0.000)
Panel B: 2SLS first stage								
Lightning strikes (log)							-0.047	-0.043
							(0.006)	(0.006)
Age group (dummies)	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Education group (dummies)	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Delegation FE	No	No	No	No	No	Yes	No	No
Std. err. clustered by delegation	Yes	No	No	No	No	No	No	No
Std. err. correction (Conley, 1999)	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Test							66.183	51.521
N	7878	7878	7878	7878	7878	7878	7878	7878
R2	0.032	0.032	0.074	0.074	0.090	0.228	0.061	0.036

Notes: Standard errors are reported in parentheses, and are clustered by delegation (column 1) or corrected for spatial correlation following Conley (1999) using a 50 km distance cutoff (columns 2-8). OLS estimates are shown in columns 1-6, and 2SLS estimates in columns 7-8. Panel A presents the estimates for the OLS and the second stage of 2SLS. Panel B reports only the coefficient for the excluded variable. Variable definitions are available in Appendix Table A1 and summary statistics in Table 1.

per square kilometer and per year over the period 1995-2010.[8] This is a strong instrument as is evidenced by the Kleibergen and Paap (2006) test (henceforth KP) statistic of 66 reported in the bottom panel of column 7 of Table 2. As was shown in Figure 1b areas buffeted by more intense lightning strikes have worse internet access. The 2SLS estimate of the impact of the internet on Daesh recruitment is statistically significant at the 10 percent level and is three times as large as its OLS counterpart. Our exclusion restriction hinges on the assumption that lightning strikes affect the propensity to join Daesh only through the availability and quality of internet. As lightning is correlated with rainfall ($\rho = 0.63$ in the data), which could affect economic development (e.g. through higher agricultural productivity), column 7 controls for averages of nighttime lights and rainfall over the period 1995-2010, which is also the time interval the instrumental variable is constructed from. Choosing lagged variables further mitigates the possibility that internet access has had an impact on nighttime lights, which could bias the first stage. In column 8, we revisit these results by controlling for delegation-level measures of radicalization into violent extremism used in column 5; if anything, doing so produces larger estimates for the effect of internet access.

Robustness Table 3 shows the results of a number of robustness checks. Where applicable, we present both OLS regression results (with delegation, age, and education fixed effects as in Table 2, column 6) in panel A and 2SLS estimates in panel B, using lightning strikes as instrument for internet access rates (as in Table 2, column 7).

We start by estimating three alternative specifications. In Table 2, column 7, we argued that satisfying the exclusion restriction requires controlling for GDP proxies and climatic data. We therefore added rainfall and nighttime light intensity variables as controls, and averaged these variables over the same time span as for the instrument, 1995-2010. We use 2014 averages instead to measure values of GDP and rainfall that are contemporaneous with the dependent variable. The estimated 2SLS coefficient for internet access (panel B, column 1), though slightly lower, is still significant at the 5 percent level. Next, we investigate whether the documented association between internet and jihadist recruitment could be driven by usage of other media.

[8] Yearly data on lightning strikes with the same level of geographical detail is not available (Manacorda and Tesei, 2020) and lightning strikes are highly serially correlated (Andersen et al., 2012).

Table 3: Robustness tests

Dependent variable	Number of Daesh recruits (inverse hyperbolic sine)							
	Alternative specifications			Sample restrictions			Spatial correlation	
	2014 values	Other media	Emi-gration	No Tunis	No mountain	No outliers	20 km radius	100 km radius
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS with delegation FE								
Internet access (rate)	0.072	0.074	0.073	0.075	0.075	0.061	0.072	0.072
	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)	(0.025)	(0.028)	(0.032)
Radio ownership (rate)		-0.020						
		(0.022)						
TV ownership (rate)		0.039						
		(0.041)						
Emigration (rate)			0.022					
			(0.031)					
N	7878	7878	7878	7248	7489	7788	7878	7878
R2	0.228	0.228	0.228	0.222	0.230	0.208	0.228	0.228
Panel B: 2SLS second stage								
Internet access (rate)	0.255	0.369	0.312	0.318	0.306	0.359	0.318	0.318
	(0.133)	(0.177)	(0.157)	(0.156)	(0.166)	(0.164)	(0.168)	(0.165)
Radio ownership (rate)		-0.058						
		(0.029)						
TV ownership (rate)		-0.041						
		(0.061)						
Emigration (rate)			0.053					
			(0.044)					
Kleibergen-Paap Test	85.730	58.512	66.124	70.412	61.072	64.488	138.982	38.306
N	7878	7878	7878	7248	7489	7788	7878	7878

Notes: Standard errors are reported in parentheses and are corrected for spatial correlation following Conley (1999) using 50 km (columns 1-6), 20 km (column 7), or 100 km (column 8) distance cutoffs. All specifications include population (log), unemployment (rate), marital status (marriage rate), area (log), age group (dummies) and education group (dummies) as controls. Column 1 further controls for 2014 nighttime lights (log) and 2014 rainfall (log), while columns 2-8 use 1995-2010 nighttime lights (log) and 1995-2010 rainfall (log) as in Table 2. Panel A reports OLS estimates, which also account for delegation FE. Panel B reports 2SLS estimates that use lightning strikes (log) as an instrument for internet access (rate). Columns 1-3 and 7-8 use the entire sample, while column 4 removes delegations in the Tunis metropolitan area (21 delegations), column 5 removes delegations with the highest coverage of mountains (13 delegations), and column 6 removes delegations with the highest number of Daesh recruits per capita (3 delegations). Variable definitions are available in Appendix Table A1 and summary statistics in Table 1.

A "horse race" between internet and TV and radio access helps to discriminate between these competing explanations. Column 2 shows the results when both radio and TV access are included in the regression: in both OLS and 2SLS specifications, neither radio nor TV access have much predictive power. In fact, the coefficient on internet access rises somewhat once these variables are included, which attests to the unique role of the internet as compared to media in general.[9] As a third potential mechanism to rule out, column 3 adds a control for emigration, to address the possibility that the association between internet access and recruitment is simply the effect of the internet on emigration. Emigration rates are however not a significant predictor of recruitment and do not affect the internet/Daesh recruitment relationship. This suggests that the mechanism by which internet access enables recruitment of international jihadists operates beyond the lowering of transaction costs.

In the next three columns, we remove potential outliers and specific geographic areas. We verify that the relationship we documented between internet access and terrorist recruitment is not driven by Tunis, the capital and most populated and connected city, from which a third of all Daesh recruits come. After delegations in the metropolitan area of Tunis are removed, column 4 indicates that the recruitment-internet correlation is still statistically significant. Column 5 excludes delegations in mountainous areas where jihadists can more easily hide from law enforcement (Zelin, 2019) and internet access is poor. Removing the delegations with mountains covering more than 85 percent of their territory or above the 95th percentile (in doing so, we adopt the Manacorda and Tesei (2020) definition of a mountainous area) does not change the result. Finally, in column 6, we check if outliers in Daesh recruitment – defined as delegations that are in the top 1 percent of the distribution of Daesh recruitment per capita– were driving our results, and they were not.

The last set of robustness checks evaluated how standard errors change when different distance cutoffs for the buffer zone are used to compute standard errors following Conley (1999). Recall that we use 50 km in the baseline specifications. Column 7 (resp. 8) shows the estimation result of the same regression with a shorter (resp. longer) radius of 20 km (resp. 100 km). Although standard errors do increase when we widen the radius, the association between internet access

[9] The same conclusions can be drawn if radio or TV access are considered separately.

and radicalization remains statistically significant at conventional levels.

Discussion Our findings resonate with anecdotal evidence on Daesh recruitment practices:[10] its strategy entailed monitoring the web to identify prospective recruits, establish first contact, cultivate personal contact and a sense of community, and culminate in a call for action (Berger, 2015). Speckhard and Ellenberg (2020), who interviewed 220 Daesh prisoners, defectors and returnees, found that internet played an important role in recruitment, with 8.2 percent of recruits claiming they were recruited *solely* over the internet. In addition, 11.8 percent mentioned the importance of internet recruiters, 22 percent mentioned being influenced by pro-Daesh content on YouTube, 10.9 percent mentioned Facebook, and 5.9 percent mentioned Twitter. Similarly, when testifying about American jihadists during a U.S. Senate hearing, Mr. Bergen, a respected national security analyst, argued "[t]he only profile that this group really shares is that 53 of the 62 individuals were very active on social media, downloading and sharing jihadist propaganda, and in some cases (...) directly communicating with members of ISIS in Syria" (United States Senate, 2015).

What do our results suggest in terms of Daesh's reliance on the internet for recruitment? To calculate the elasticity of enrollment in the terror group with respect to internet access rates, we use the fixed-effect specification in Table 2, column 4, which yields a more conservative estimate than the larger estimates obtained using 2SLS. Because our left-hand side variable is the inverse hyperbolic sine transformation of the number of Daesh recruits, the regression coefficient does not have a straightforward elasticity interpretation, especially since in our sample the median delegation in Tunisia has zero Daesh recruits. To compute an elasticity, we calculate for each $\{dea\}$ cell how the number of recruits would increase if internet access increased by one percent. The resulting change in (the ihs of) the number of recruits is given by $\Delta asinh(R_{dea}) = \alpha Internet_{dea} \times 0.01$. The elasticity of Daesh recruitment with respect to internet access rates is thus $\varepsilon = \frac{1}{.01} \times \frac{\sum sinh[R_{dea} + \alpha Internet_{dea} \times 0.01]}{\sum R_{dea}}$. With an estimated $\hat{\alpha} = 0.072$

[10] Daesh was very active in online forums; it also maintained a well-read online magazine (Dabiq) and various blogs encouraging readers to travel to Syria and Iraq to join the jihad and offering tips on how to travel and avoid getting caught. It also had a strong social media presence (Bloom et al., 2017; Conway et al., 2019). By 2014, at least 46,000 Twitter accounts were overtly supporting Daesh (Berger and Morgan, 2015) and in 2015 Daesh issued over 17 million tweets, about 0.2 percent of all Arabic twitter content. Daesh is also infamous for its graphic footage of beheadings and violent attacks, which were widely viewed, with over 20 percent of the U.S. population having watched at least part of an ISIS video (Redmond et al., 2019).

(Table 2 column 5), a one percent increase in the rate of internet access by Tunisian men increases the total number of recruits in the sample by an estimated 2.6 individuals, which, with a sample size of 468 recruits, yields a .56 elasticity. Our quantitative results thus complement qualitative accounts on the importance of the internet for Daesh recruitment of foreign fighters.

5 Conclusion

By allowing new forms of social interaction and acquisition of information the internet has fundamentally reshaped society. While it is often a force for development, this paper presents evidence that it has also been accompanied by the rise of violent extremist groups such as Daesh, the epitome of tech-savvy terrorism. After combining administrative data from the international jihadist organization with census data from Tunisia, we document quantitatively that the internet has been, on net, a potent facilitator of international terrorist recruitment. Our analysis suggest a 0.56 elasticity of Daesh recruitment with respect to internet access, attesting to the proclivity of transnational terror organizations to (ab)use cutting-edge information and communication technologies.

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A Supplemental material [online version only]

Table A1: Variable descriptions

Variable	Description	Source
Panel A: Delegation-age-education $\{d, e, a\}$ level variables		
Age group (dummies)	Dummy variables indicating which age group a individuals in a given $\{d, e, a\}$ cell belong to. There are 10 different groups, notably: (i) 15-19 years, (ii) 20-24 years, (iii) 25-29 years, (iv) 30-34 years, (v) 35-39 years, (vi) 40-44 years, (vii) 45-49 years, (viii) 50-54 years, (ix) 55-59 years, and (x) 60 years or more.	The 2014 Tunisia Census of Population and Housing (INS)[a]
Education group (dummies)	Dummy variables indicating which level of education e individuals in a given $\{d, e, a\}$ cell have completed. There are 3 different groups, notably: (i) primary or below, (ii) secondary, and (iii) tertiary.	The 2014 Tunisia Census of Population and Housing (INS)[a]
Internet access (rate)	Share of men in the $\{d, e, a\}$ cell that used the internet in the last 3 months	The 2014 Tunisia Census of Population and Housing (INS)[a]
Married (rate)	Share of men in the $\{d, e, a\}$ cell that are married	The 2014 Tunisia Census of Population and Housing (INS)[a]
Number of Daesh recruits	Number of individuals in the $\{d, e, a\}$ cell who joined Daesh in Syria or Iraq between 2013 and 2014. Note that the personnel records only present information on male recruits.	Daesh personnel records
Population	Number of men in the $\{d, e, a\}$ cell	The 2014 Tunisia Census of Population and Housing (INS)[a]
Radio ownership (rate)	Share of men in the $\{d, e, a\}$ cell that own a radio	The 2014 Tunisia Census of Population and Housing (INS)[a]
TV ownership (rate)	Share of men in the $\{d, e, a\}$ cell that own a TV	The 2014 Tunisia Census of Population and Housing (INS)[a]
Unemployment (rate)	Share of men in the $\{d, e, a\}$ cell that are unemployed	The 2014 Tunisia Census of Population and Housing (INS)[a]
Panel B: Delegation d level variables		
Area	Geographical area of each delegation d in km^2. Douz North and Douz Sud are combined into one administrative division.	Author's calculations based on HDX-OCHA[b]
Convicted terrorists	Number of individuals indicted for terrorist crimes committed between 2004 and 2018 from delegation d. The records include their addresses, which allows us to geolocate them.	National List of Persons, Organizations and Entities Associated with Terrorist Crime (CNLCT, 2021)[c]
Emigration (rate)	Share of men from delegation d that emigrated abroad.	The 2014 Tunisia Census of Population and Housing (INS)[a]

Internet access (rate)	Share of men in the delegation d that used the internet in the last 3 months.	The 2014 Tunisia Census of Population and Housing (INS)[a]
Islamist vote (share)	The share of votes in the 2014 Legislative Elections for Ennahda, the main Islamist party in Tunisia, in delegation d.	Author's compilation from ISIE (2015)[d]
Jihadist lectures (dummy)	Dummy variable that assumes value 1 if Ansar al-Sharia Tunisia (AST) leadership delivered jihadist religious lectures between 2011 and 2016 in the delegation d, and 0 otherwise.	Author's compilation from Zelin (2020)[e]
Lightning strikes	Average annual intensity of lightning strikes per square km for the 1995-2010 period in a given delegation d.	Manacorda and Tesei (2020)
Married (rate)	Share of men in delegation d that are married	The 2014 Tunisia Census of Population and Housing (INS)[a]
Mountains (share)	The share of the area in delegation d covered by mountains. We calculate the fraction of mountains within a delegation as the share of grid cells within the administrative division that are covered by one of the following three categories of mountains: (1) the elevation is between 1000 and 1500 meters with either a slope of at least 5 degrees or a local (i.e. within a 7 km radius) elevation range exceeding 300 meters, (2) elevation exceeding 300 but lower than 1000 meters and a local (7 km radius) elevation range exceeding 300 meters, and (3) Inner isolated areas ($\leq$ 25 sq.km in size) that do not meet criteria (1) or (2) but are surrounded by mountains.	Author's calculations based on Mountains of the World 2002 (UNEP-WCMC, 2002)[f]
Nighttime lights	Total sum of the average annual delegation d level nighttime light intensities for the 1995-2010 period and for the year of 2014. Li et al. (2020)'s dataset contains annual time series data. Intensities are expressed in digital numbers.	Author's calculations based on the Harmonized Global Nighttime Light dataset 1992-2018 (Li et al., 2020)
Number of Daesh recruits	Number of individuals in delegation d who joined Daesh in Syria or Iraq between 2013 and 2014. Note that the personnel records only present information on male recruits.	Daesh personnel records
Population	Number of men in delegation d	The 2014 Tunisia Census of Population and Housing (INS)[a]
Protests and riots	Cumulative number of political protests and riot events that took place between 2011 and 2014 in delegation d.	ACLED[g] (Raleigh et al., 2010)
Radio ownership (rate)	Share of men in delegation d that own a radio	The 2014 Tunisia Census of Population and Housing (INS)[a]
Rainfall	Average monthly rainfall in mm for delegation d for the 1995-2010 period and for the year 2014. The GPCC dataset (2015) contains monthly time series data and is aggregated according to the period/year being analyzed.	Author's calculations based on the GPCC dataset[h] (Schneider et al., 2015)
Turnout (share)	The share of eligible voters in the 2014 Legislative Elections that cast a vote in delegation d.	Author's compilation from ISIE (2015)[d]

TV ownership (rate)	Share of men in delegation d that own a TV	The 2014 Tunisia Census of Population and Housing (INS)[a]
Unemployment (rate)	Share of men in delegation d that are unemployed	The 2014 Tunisia Census of Population and Housing (INS)[a]

Notes: [a] The 2014 Tunisia Census of Population and Housing was conducted by L'Institut National de la Statistique (INS). [b] Tunisia administrative boundaries for delegations are obtained from The Humanitarian Data Exchange (HDX) and produced by The United Nations Office for the Coordination of Humanitarian Affairs (OCHA). Date of access: March 20, 2019 [link]. [c] The National List of Persons, Organizations and Entities Associated with Terrorist Crime is produced by La Commission Nationale de Lutte Contre le Terrorisme (CNLCT, 2021). Date of access: April 19, 2021 [link].[d] Elections in Tunisia are conducted by the Instance Supérieure Indépendante pour les Elections ISIE (2015). Date of access: September 20, 2021 [link]. [e] The Ansar al-Sharia in Tunisia's Clerical Establishment dataset is described in Zelin (2020). Date of access: March 25, 2021 [link]. [f] The Mountains of the World 2002 dataset, produced by The UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC), is described in UNEP-WCMC (2002). Date of access: April 28, 2021 [link]. [g] The Armed Conflict Location and Event Data Project (ACLED) is described in Raleigh et al. (2010) [h] The precipitation data are produced by the Global Precipitation Climatology Centre (GPCC) and described in Schneider et al. (2015). Date of access: April 28, 2021 [link].

Table A2: Tests of sample selection

	Analysis sample			Left-out sample			Difference		Joint Test
Variable	N	Mean	Std. Err.	N	Mean	Std. Err.	Diff	Std. Err.	F-stat.
Education group									1.502
Primary or below (dummy)	468	0.241	0.020	114	0.167	0.035	0.075	0.044	
Secondary (dummy)	468	0.506	0.023	114	0.544	0.047	-0.037	0.052	
Tertiary (dummy)	468	0.252	0.020	114	0.289	0.043	-0.037	0.046	
Age group									3.067
15-24 years (dummy)	468	0.038	0.009	118	0.102	0.028	-0.063	0.023	
20-24 years (dummy)	468	0.327	0.022	118	0.144	0.325	0.183	0.019	
25-29 years (dummy)	468	0.368	0.022	118	0.432	0.046	-0.065	0.050	
30-34 years (dummy)	468	0.162	0.017	118	0.169	0.035	-0.007	0.038	
35-39 years (dummy)	468	0.058	0.011	118	0.093	0.027	-0.036	0.025	
40-44 years (dummy)	468	0.019	0.006	118	0.034	0.017	-0.015	0.015	
45-49 years (dummy)	468	0.009	0.004	118	0.008	0.008	0.000	0.009	
50-54 years (dummy)	468	0.004	0.003	118	0.000	0.000	0.004	0.006	
55-59 years (dummy)	468	0.000	0.000	118	0.008	0.008	-0.008	0.004	
60 or more years (dummy)	468	0.015	0.006	118	0.008	0.008	0.006	0.012	
Occupation									0.715
Employer/Manager (dummy)	459	0.007	0.004	128	0.008	0.008	-0.001	0.008	
Professional (dummy)	459	0.220	0.019	128	0.227	0.037	-0.007	0.042	
Manual worker (dummy)	459	0.126	0.016	128	0.180	0.034	-0.053	0.034	
Agricultural worker (dummy)	459	0.031	0.008	128	0.016	0.011	0.015	0.016	
Military and security (dummy)	459	0.002	0.002	128	0.008	0.008	-0.006	0.006	
Owner of a shop (dummy)	459	0.039	0.009	128	0.039	0.017	0.000	0.019	
Government employee (dummy)	459	0.007	0.004	128	0.000	0.000	0.007	0.007	
Private sector employee (dummy)	459	0.255	0.020	128	0.250	0.038	0.005	0.044	
Craftsperson (dummy)	459	0.102	0.014	128	0.055	0.020	0.048	0.029	
Illegal (dummy)	459	0.002	0.002	128	0.000	0.000	0.002	0.004	
Student (dummy)	459	0.129	0.016	128	0.156	0.032	-0.028	0.034	
Retired (dummy)	459	0.002	0.002	128	0.000	0.000	0.002	0.004	
No work (dummy)	459	0.078	0.013	128	0.063	0.021	0.016	0.026	
Civil Status									1.538
Divorced (dummy)	391	0.010	0.005	123	0.000	0.000	0.010	0.009	
Married (dummy)	391	0.179	0.019	123	0.236	0.038	-0.057	0.041	
Single (dummy)	391	0.811	0.020	123	0.764	0.038	0.047	0.041	
Religious knowledge									1.230
Basic (dummy)	407	0.705	0.023	113	0.779	0.039	-0.074	0.048	
Intermediary (dummy)	407	0.265	0.022	113	0.204	0.038	0.062	0.046	
Advanced (dummy)	407	0.029	0.008	113	0.018	0.012	0.012	0.017	
Experience with Jihad									0.161
No (dummy)	432	0.951	0.010	125	0.960	0.018	-0.009	0.021	
Yes (dummy)	432	0.049	0.010	125	0.040	0.018	0.009	0.021	

Notes: Variables are constructed from self-reported information provided by recruits that is available in the Daesh personnel records database. The "analysis" sample consists of observations included in the analysis; the "left-out" sample consists of observations dropped because of missing information on either delegation of residence, education, or age. In the last column, for each group of variables, the F-statistic reports the result of a test of joint significance of all variables in that group.

Table A3: Alternative transformations of the dependent variable

Dependent variable:	Number of Daesh recruits			
	ihs	linear	log (1+...)	dummy
	(1)	(2)	(3)	(4)
Panel A: OLS with delegation FE				
Internet access (rate)	0.072	0.121	0.056	0.048
	(0.028)	(0.047)	(0.022)	(0.021)
N	7878	7878	7878	7878
R2	0.228	0.207	0.228	0.216
Panel B: 2SLS second stage				
Internet access (rate)	0.318	0.555	0.247	0.217
	(0.159)	(0.264)	(0.123)	(0.123)
N	7878	7878	7878	7878
Kleibergen-Paap test	66.183	66.183	66.183	66.183

Notes: Standard errors are reported in parentheses and are corrected for spatial correlation following Conley (1999) using a 50 km distance cutoff. All specifications control for population (log), unemployment (rate), married (rate), area (log), 1995-2010 nighttime lights (log), and 1995-2010 rainfall (log). Panel A presents OLS estimates, which also account for delegation FE. Panel B presents 2SLS estimates that use lightning strikes (log) as an instrument for internet access (rate). Column 1 replicates the baseline result in Table 2 with the inverse hyperbolic sine transformation of the number of Daesh recruits as dependent variable. Column 2 simply uses the number of Daesh recruits as dependent variable. Column 3 takes the logarithm of 1 + the number of Daesh recruits as dependent variable. Column 4 uses as dependent variable a dummy variable that assumes value 1 if the number of Daesh recruits is strictly positive, and 0 otherwise. Appendix Table A1 provides complete definitions of variables and Table 1 displays summary statistics.