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Communications Technology and Terrorism

Abstract

By facilitating the flow of information in society, communications technology (CT; e.g., newspapers, radio, television, the internet) can help terrorists to (i) spread their message, (ii) recruit followers, and (iii) coordinate among group members. However, CT also facilitates monitoring and arresting terrorists. This paper formulates the hypothesis that a society's level of CT is systematically related to terrorism. We introduce a simple theoretical framework, suggesting that terrorism first becomes more attractive with a rise in CT, but then decreases, following an inverted U-shape. Accessing data for 199 countries from 1970-2014, we find evidence for these predictions: Terrorism peaks at intermediate ranges of CT and corresponding magnitudes are sizeable. Our estimations control for a range of potentially confounding factors, as well as country- and year-fixed effects. Results are consistent throughout a battery of robustness checks and placebo regressions. Finally, we find no evidence of a potential reporting bias explaining our findings.

JEL-Codes: D740, D830, L820, L860, L960, P160.

Keywords: communications technology, GTD, information flows, terrorism, panel data.

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[U]nlike their predecessors, contemporary terrorists operate in a global information and communication environment with opportunities for mass self-communication that earlier terrorists could not have imagined. (Nacos, 2016, in *Mass-mediated terrorism*)

1 Introduction

In virtually every definition of terrorism, the communication of a message to a target audience plays a key role.[1] In most terrorist attacks, those who directly lose their lives are not the primary victims – they merely serve as a communication tool between the terrorists and an audience. Realizing this fundamental characteristic of terrorism carries a simple corollary: If information does not flow from the terrorist group to the target audience, and is not distributed well among that audience, an attack fails its purpose of (*i*) spreading the group's message, (*ii*) creating fear in a target population, and (*iii*) recruiting followers (see Wilkinson, 1997, Pries-Shimsh, 2005, Frey et al., 2007, or Walsh, 2010, for these goals of terrorist attacks). Beyond these goals, information flows also become important for a terrorist group's financing, planning, and execution of attacks (see Stenersen, 2008, Jacobson, 2010, Theohary, 2011, and Nacos, 2016).

Over the past decades, the flow of information, i.e., the ease and speed with which information travels through society, has been transformed in virtually every country as never before. This trend has been crucially driven by communications technology (CT from hereon; e.g., newspapers, radio, television, or the internet) to facilitate and accelerate the free flow of information (see Harvey, 1989, and Castells, 2008, 2011). However, even though terrorism as an explicit communication tool has been employed as early as 2,000 years ago (e.g., see Malamat et al., 1976), we still have little empirical evidence on potential links between the degree of information flows in a society and terrorism. In the following pages, we propose the occurrence of terrorism to be intimately linked to the state of CT.

[1] For example, Frey and Luechinger (2003) and Frey et al. (2007) suggest terrorists are seeking publicity "in order to make their cause widely known"; the Britannica Concise Encyclopaedia suggests that "[t]errorism's impact has been magnified by the...capability of the media to disseminate news of such attacks instantaneously throughout the world" (Britannica, 2006); and section 2656f(d) of the US Code of Laws emphasizes terrorists' goal of "influencing an audience" (Nacos, 2016).

We begin by formulating a simple theoretical model to understand how the existing level of CT may influence a potential terrorist's decisions. Our aim here is to provide the most basic framework that builds on few, but simple assumptions in framing a representative agent's choice between engaging in terrorism and participating in the labor market. The theoretical implications suggest that as CT improves terrorism first increases, but later diminishes, following an inverted U-shape. To check whether these propositions can be observed in reality, we study a sample of up to 199 countries from 1970 to 2014. Specifically, we connect the KOF index of information flows to the number of terrorist attacks in a given country and year. The corresponding results indeed document a bell-shaped relationship. Interestingly, this relationship holds (*i*) after considering a range of potentially confounding factors, as well as country- and year-fixed effects, (*ii*) for domestic and transnational terrorism alike, and (*iii*) across a range of additional robustness checks.

We also show why, perhaps, previous empirical studies have focused less on information flows since a purely linear specification produces a coefficient that is not statistically significant on conventional levels. However, as soon as our suggested nonlinearity is accounted for, the relationship becomes statistically significant on the one percent level. Terrorism is suggested to peak in countries with moderate levels of information flows, everything else equal. In reality, this corresponds to countries with a KOF score in the range of 0.44 to 0.56, examples of which are India, Nigeria, Kenya, Bangladesh, or Yemen in 2014. To give an idea about the associated magnitudes, our results would imply that improving a KOF score of 0.45 (e.g., Bhutan in 2014) to 0.55 (e.g., Sri Lanka in 2014) corresponds to a rise in terrorist attacks by 2.8 percent. However, raising CT by another ten percentage points, from 0.55 to 0.65 (e.g., to the level of the Dominican Republic in 2014), would relate to a *decrease* in the number of terrorist attacks by five percent. Thus, the suggested magnitudes are sizeable and, as we show in the paper, larger than the suggested relationship between democracy and terrorism, for example (see Figure 4).

Overall, we aim to contribute to two distinct streams of research. First, our results speak to our understanding of what can drive terrorism. As CT has improved – from newspapers over the radio to television, the internet, and now social media – our results suggest that these conditions may be intimately linked to terrorism, everything else equal. The closest existing research to our hypothesis considers the link between *press freedom* and terrorism (see Li, 2005, Chenoweth, 2010, 2012, 2013, Hoffman et al., 2013, Asal and Hoffman, 2016, and Bakker et al., 2016). Although the regulatory freedom of the press can play an important role for terrorism in its own right, such characteristics form only a subset of our general concept of information flows presented here. Another related line of scientific inquiry considers the link between *media coverage* of terrorism and subsequent attacks (e.g., see Nelson and Scott, 1992, Scott, 2001, Rohner and Frey, 2007, and Jetter, 2014, 2017a,b,c). The underlying hypotheses here, also, consider a subset of our concept of information flows. Thus, we believe this paper is the first to systematically formulate a general relationship between CT and terrorism with an empirical assessment of this hypothesis.

Second, this paper speaks to the literature concerning consequences of technological improvements, in particular those related to CT. Although a number of works are proposing and documenting substantial gains in terms of productivity and output growth from improved CT (see Brynjolfsson and Hitt, 2000, Schreyer, 2000, Black and Lynch, 2001, Radjou, 2003, and Timmer and Van Ark, 2005), some studies suggest these developments also carry societal costs (Kiesler et al., 1984, Kraut et al., 1998, and Silverstone, 2017). Our findings imply that improved CT in initial phases may make terrorism more attractive as a strategy to communicate grievances. However, once CT has crossed a threshold, further advancements are suggested to diminish terrorism.

The paper proceeds with a brief section to motivate our analysis of CT and terrorism. We then introduce our theoretical intuition, followed by a description of our data and methodology in Section 4. Section 5 describes our main empirical findings with the associated robustness checks and extensions. Finally, Section 6 concludes.

2 Background

Before introducing a formal model, we want to describe a range of real-life observations in which terrorists themselves have indicated that information flows in different forms play a role in their actions. In general, this intuition is built on two basic mechanisms. First, our theoretical setup is based on the idea that improved CT can be conducive to the terrorists' goals of (i) spreading their message, (ii) creating fear in a target population, and (iii) recruiting followers. Further, better CT facilitates coordination *between* members of a potential terror group. Second, we start from the premise that CT systematically improves the state's policing capacity, everything else equal, which in turn increases the likelihood of catching perpetrators. We now provide anecdotal evidence for both mechanisms before turning to our formal model.

2.1 Communications Technology as a Facilitator for Terrorism

While early terrorists had to rely on face-to-face communication or printed material that requires time and costly dissemination, modern terrorists have quick and reliable communication channels at their disposal that let them communicate instantaneously to thousands at negligible costs (Zanini and Edwards, 2001). For example, it may not be a coincidence that the Salafi jihad movement began during an age of a revolution in CT in the 1990s (Sageman, 2004). Arquilla et al. (2000) suggest that CT developments allow the transition from a hierarchial to a network-based organizational structure that benefits non-state actors and extends their reach internationally. Notably, al-Qaeda appeared to employ the internet for 'cyberplanning' (Thomas, 2003) and later terrorist organizations use the internet in even more refined ways. For instance, the Islamic State of Iraq and Syria (ISIS) publishes online magazines (e.g., *Dabiq* and *Rumiyah*) that (i) provide volumes on their ideology, (ii) encourage readers to contribute financially, (iii) teach their followers how to conduct terrorist attacks, and (iv) provide links to assassination videos conducted by their members. Crucially, modern CT tools allow them to bypass the gatekeepers of traditional media.

The features of borderless communication, anonymity, and far-reaching transmission have made the internet a key element in the mechanics of terrorism (Rogan, 2006). In fact, the online dissemination of victim and assassination videos have been identified as some of the most powerful tools to promote radical extremism (e.g., see Alonso and Reinares, 2006, Holt et al., 2015, and Danzell and Montañez, 2016). In one of the latest developments, communication applications let perpetrators broadcast their attacks live. For example, in a terrorist attack in Pakistan on December 1, 2017, the perpetrators broadcasted the attack live to their handlers via smartphones attached to their bodies (see Ali, 2017, for details).

Although we generally know little about individual terrorists and their backgrounds, the few existing databases provide further reason to explore a systematic link to CT. For instance, in the *PIRUS* dataset (*Profiles of Individuals Radicalized in the US*), 252 out of the 495 individuals (or more than 50 percent) for whom data are available, indicate that the internet or other media played a substantial role in their radicalization. 44 percent of the 156 individuals for whom data are available used the internet as a means for executing their respective plots. In another dataset on *Profiles of Perpetrators of Terrorism in the US* (*PPT-US*), 33 of the 48 groups for which this information is recorded use political pronouncements and exhortations through newspapers, radio, television, and the web as a medium of recruitment.

As a concrete example, consider the London bombings of July 7, 2005, in which the internet was used to carry out terrorist attacks by the 'self-starter' autonomous cliques (Kirby, 2007). The official report on these bombings stated that the "London attacks were a modest, simple affair by four seemingly normal men using the internet" (Townsend, 2006). Motivated by internet-based propaganda and inspired by al-Qaeda ideology, the terrorists followed "the recipe to make a bomb...as available on the Internet as a recipe for meatloaf" (Savage, 2005). As another example, the self-radicalization phenomenon among the Saudi youth is believed to have emerged at the same time as the internet arrived in Saudi Arabia in 1999 (Hegghammer, 2006).

Finally, we want to briefly discuss the case of Momin Khawaja – a Canadian citizen sentenced for giving material support to terrorism. McCauley et al. (2016) document that Khawaja took his oath of allegiance to a radical group, the Ansaar Youth Organization, through their website. The website also invoked its subscribers to collect funds for jihad. Zenab Armandpisheh, a university student in the US was identified as a potential source of finance by the terrorists belonging to the Ansaar Youth Organization through her interactions in a chat room and she was later deceived into transferring funds multiple times to the account of the terrorist organization with the help of a series of email conversations. In the days just before his arrest, Khawaja along with another terrorist, used a public computer in an internet café to access an electronic device that could be used for remote bomb detonation.

Although these anecdotes suggest that CT played an important role in a range of different terrorism settings, they of course remain descriptive.

2.2 Communications Technology and Policing Efforts

McCauley et al.'s (2016) case study also discusses how the police have employed CT to tighten their grip on the terrorists. In fact, the British authorities identified Khawaja as a potential terrorist by tracking his internet activity. Soon after, they retrieved detailed information about him and "[w]ith a few quick calls to Canada, the investigation also became a national priority in Canada. Momin Khawaja would be subjected to 24 hour a day surveillance as soon as he was back on Canadian soil. His every action and communication would be monitored and recorded."

Similarly, the identification of the London bombers was made possible by closed circuit television (CCTV); the investigators analyzed 2,500 pieces of CCTV footage to track the bombers walking to the attack site with their backpacks (Wright and Singer, 2014). A plan of suicide bombings in the Hudson river train tunnels in 2006 was averted by identification of the Lebanese planner, Assem Hammoud, in an internet chatroom (Baker and Rashbaum, 2006). In September 2009, a planned attack on the Dallas skyscraper in Texas was foiled when police arrested a 19 year old, Hosam Majer Husein Smadi, who was under surveillance since he was identified as an extremist by his online conversations (Dahl, 2011). Reportedly, various interceptions in terrorists' communications have helped prevent terror attacks in the U.S. (Lister and Cruickshanck, 2013).

Thus, CT may not only facilitate terrorist acts, but also the possibility to persecute and arrest (potential) perpetrators (e.g., see Pattavina, 2005). It is important to check whether this assumption is reasonable and reflected in reality. Specifically, if the link between CT and the probability of getting caught were linear, we should be able to observe that relationship in the existing data. Although exact data on the likelihood of getting caught are unavailable, the Global Terrorism Database (GTD; see Section 4.1.1 for a proper description of these data) allows us to consider the number of successful attacks as a fraction of all attacks. Among other reasons, attacks in which the perpetrators were caught on their way to commit an attack are included in the unsuccessful attacks.[2] The results are visualized in Figure 1, where we plot the ratio of successful attacks in a given country and year to the KOF index of information flows, which will form our primary measure for CT (see Section 4.1.2). The negative and primarily linear relationship suggests that improvements in CT systematically increase the state's capacity of foiling a terrorist attack.

With these two basic mechanisms in mind, we now turn to a formal analysis of the link between CT and terrorism.

3 Theoretical Framework

3.1 Assumptions

Our model is based on Becker's (1968) seminal work on crime. Specifically, imagine one representative agent who is contemplating whether to invest their time in terrorism (denoted by β with $0 \leq \beta \leq 1$) or in the labor market $(1 - \beta)$. Without loss of generality, we ignore leisure time. Further, a parameter τ (with $0 \leq \tau \leq 1$) represents the degree of CT in society, where $\tau = 0$ corresponds to a society without any type of communication, i.e., not even talking to one's neighbor.[3] As τ rises, news travels faster and wider. For example, the invention and introduction of the newspaper, the radio, television, the internet, and social media all constitute

[2] Note that not all unsuccessful attacks listed in the GTD were foiled because of an intervention by law enforcement. Other reasons include (i) the bomb did not detonate, (ii) the target was missed, and (iii) hostage takers could not take control of the individual. However, it is difficult to imagine how these causes can be systematically correlated with the existing degree of CT. Unfortunately, we do not have attack-wise information on the exact reason for failure of the attack.

[3] In an extreme scenario, this would correspond to the Khmer Rouge's envisioned society, for example (Kiernan, 1972).

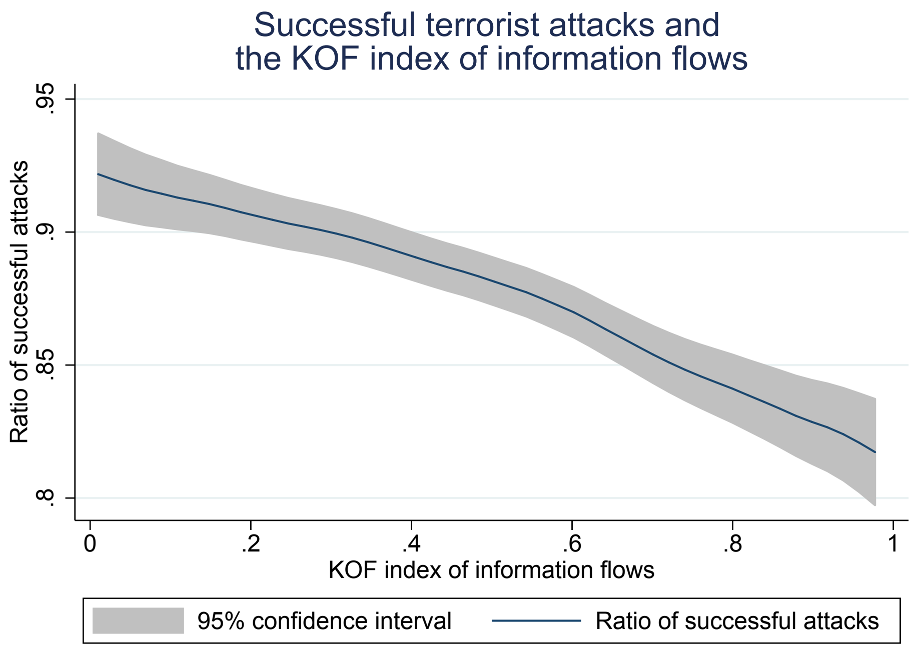

Figure 1: Plotting the ratio of successful terrorist attacks ($= \frac{successful\, attacks}{successful+unsuccessful\, attacks}$) against the KOF index of information flows for all 3,535 country-year observations that experienced at least 1 terror attack from 1970-2014.

milestones that would be associated with a substantial rise in τ; so would their more widespread availability and usage.

The agent maximizes their profit function, π, which depends on their expected returns from terrorism and work. First, $F(\beta, \tau)$ constitutes the agent's production function for terrorism, which we assume to satisfy the Inada conditions, i.e., $F(i, 0) = 0$, $\frac{\partial F}{\partial i} > 0$, $\frac{\partial^2 F}{\partial i^2} < 0$, $\lim_{i \to 0} \frac{\partial F}{\partial i} = \infty$, and $\lim_{i \to \infty} \frac{\partial F}{\partial i} = 0$, $\forall i \in \{\beta, \tau\}$. Intuitively, more investment in terrorism yields larger returns and so does better CT; however, returns from both are increasing at a decreasing rate. Thus, as investment in terrorism increases (i.e., one can imagine more and bigger attacks), the marginal benefit decreases, as less and less is gained from an additional attack. Similarly, the higher the level of technological advancements in communication, the smaller the marginal benefit from an additional innovation. For instance, when people watch the news on television about a terrorist attack, looking at the same news content on the internet may increase the psychological impact, but the incremental increase in spreading information becomes smaller as CT improves. Put differently, receiving news for the first time carries a larger effect than getting the same story again via different means of communication. A similar intuition follows from the terrorists' perspective. In terms of communicating with fellow group members (e.g., to coordinate a strike), the returns from communicating at a faster pace with better technology are more than returns from communicating at a slower pace, but as CT improves the marginal gains become smaller.

The overall returns from terrorism also depend on the success of the operation: If the agent gets caught by the policing authority, we assume they will not be able to reap the benefits from their terrorism investment.[4] We assume the likelihood of getting caught, p, to be proportional to changes in CT, consistent with the existing literature about the link between information technology and crime prevention (e.g., see Fazlollahi and Gordon, 1993, Braga et al., 1999, Braga, 2001, Pattavina, 2005, and Byrne and Marx, 2011). Thus, a higher τ increases the

[4]Without loss of generality, one could change this assumption and assume non-negative returns even after the terrorist is caught. Further, in reality, the punishment for engaging in terrorism may impose large *negative* returns on the terrorist. However, the essence of the model's conclusions would remain unaffected if we adjusted the payoff structure in either direction.

probability of getting caught linearly, i.e., $p = p(\tau)$, where $\frac{\partial p}{\partial \tau} > 0$ and $\frac{\partial^2 p}{\partial \tau^2} = 0$.

Lastly, we assume that the agent can earn an exogenously given non-negative wage, w (with $w \geq 1$), in the formal labor market. Formally, we can then write the profit function of our representative agent as

$$\pi(\beta) = \big[1 - p(\tau)\big] \times F(\beta, \tau) + (1 - \beta)w. \tag{1}$$

With this description of profits in mind, we now turn to a specific functional form of $F(\cdot)$ to maximize π.

3.2 Maximizing Profits

What we are ultimately interested in is whether and, if so, how CT (τ) influences the agent's choice with respect to terrorism (β). In order to investigate that relationship, we now transform equation 1 to its simplest operable functional form:

$$\pi(\beta) = \big(1 - \tau\big)\big(\beta\tau\big)^{\alpha} + (1 - \beta)w, \tag{2}$$

where $0 < \alpha < 1$ satisfies our first- and second-order conditions introduced above.[5] The agent then chooses β to maximize π, which leads to the equilibrium investment of

$$\beta^* = \left[\frac{\alpha\tau^{\alpha}(1 - \tau)}{w}\right]^{\frac{1}{1-\alpha}}. \tag{3}$$

Because $0 \leq \tau \leq 1$ and $0 < \alpha < 1$, β^* is naturally bound between zero and one. Note that one can derive corner solutions of $\beta^* = 0$ for *both* extreme cases of $\tau = 0$ and $\tau = 1$. The latter case may be comparable to the 'singularity' sometimes discussed among futurists (e.g., see Kurzweil, 2005): Any new piece of information becomes instantly available to everyone.

Equation 3 tells us that an increase in returns from the formal labor market (w) decreases the optimal time devoted to terrorism. Further, we can conduct comparative statics along the

[5] It is worth mentioning that by leaving β and τ to be governed by the same exponent α, we are forcing the two to behave similarly. Our results, however, do not change if we relax this assumption. See appendix A.1 for this alternative specification.

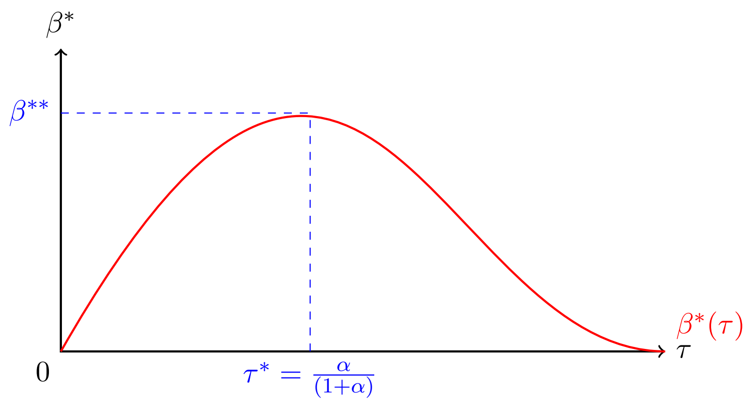

Figure 2: The impact of communications technology on the optimal fraction of time devoted to terrorism (β^*).

lines of τ – how does a change in CT affect the extent of terrorism? With a bit of algebra, we can show that finding the value of τ associated with maximum point of β (i.e., β^{**}) via $\frac{\partial \beta^*}{\partial \tau} = 0$ produces[6]

$$\tau^* = \frac{\alpha}{1+\alpha}. \tag{4}$$

Since $0 < \alpha < 1$, τ^* constitutes a nonnegative value. Figure 2 visualizes the relationship between τ and β^*. Initially, with an improvement in CT, the agent devotes more time to terrorism, i.e., better technology would imply more terrorism, everything else equal. Intuitively, an attack earns more publicity and has therefore more impact when information flows better; in addition, internal coordination between the infinitesimal group members becomes easier. However, engaging in terrorism loses its relative profitability beyond τ^*, as the gains from earning w begin to outweigh the decreasing net returns to terrorism since the likelihood of apprehension gains strength. In sum, our simple theoretical framework suggests a nonlinear relationship between the degree of information flows (i.e., the available CT) and the extent of terrorism. At low values of τ, we

[6]The proof that τ^* constitutes a maximum, not a minimum, is referred to Section A.2 in the appendix.

should expect a positive relationship, but after τ^* is reached, the link should turn negative. The quantification of τ^* remains an empirical question that we will investigate in the upcoming sections.

4 Data and Empirical Methodology

We begin by describing our data sources for terrorism and information flows, the key variables in our empirical analysis. Our aim is to carefully relate our theoretical hypothesis to existing empirical analyses that focus on related concepts. We then move to explaining our set of control variables, as suggested by the existing literature. All variables included in our study are summarized in Table 1 along with their corresponding sources and definitions. Finally, we introduce our econometric strategy.

4.1 Data

4.1.1 Data on Terrorism

We access data on terrorist attacks from what has become the standard source for empirical research on terrorism: The Global Terrorism Database (*GTD*, START, 2016).[7] The *GTD* is maintained and updated annually by the "National Consortium for the Study of Terrorism and Responses to Terrorism" (*START*), based at the University of Maryland. We employ the latest version of the GTD, covering over 170,000 incidents from 1970 to 2014.[8] The *GTD* offers a detailed list of variables related to each attack, such as the number of victims (dead and otherwise affected), the target, and whether the attack can be categorized as domestic or international terrorism.

[7]Recent papers employing the *GTD* come from Krieger and Meierrieks (2010), Berrebi and Ostwald (2011, 2013), Derin-Güre (2011), Dreher et al. (2011), Findley and Young (2011), Freytag et al. (2011), Gaibulloev and Sandler (2011), Pfeiffer (2012), Chenoweth (2013), Choi and Salehyan (2013), Piazza (2013), Wilson and Piazza (2013), Kis-Katos et al. (2014), Brockhoff et al. (2015), Bakker et al. (2016), and Gaibulloev et al. (2017).

[8]Note that, as is well-known in the literature and stated in the *GTD* codebook, the *GTD* does not include any information for the year 1993 (see LaFree and Dugan, 2007, Lee, 2008, and LaFree, 2010). Thus, we exclude 1993 from our analysis.

Our main outcome variable measures the number of terrorist attacks in a given country and year. We begin by analyzing all attacks, but then also split the sample into those categorized as domestic or international by the *GTD* and Enders et al. (2011).[9]

One point of concern is that the GTD, as many other publicly available databases, collects information from open data sources. Thus, it is possible that some attacks remain undetected if they are never reported or documented anywhere, i.e., when information flows are limited to begin with. For example, Drakos and Gofas (2006a, 2007) suggest an underreporting bias in countries where the media is not free. Although a concern for any empirical study of terrorism, this is of particular importance in our setting since our hypothesis states precisely that *information flows* can systematically influence terrorism. Although it remains difficult to completely dispel such concerns, we pursue several avenues to test for this possibility.

First, a range of studies argue that the likelihood of a systematic bias in media-based event count data becomes much smaller if the data (*i*) cover hard facts (Franzosi, 1987), (*ii*) concern significant violent events (Schrodt, 1994), or (*iii*) are gathered from a large number of sources (Woolley, 2000). The first two criteria are intuitively satisfied with respect to terror attacks. To comply with these conditions more clearly, we conduct alternative estimations where we (*i*) only focus on attacks that produce fatalities, (*ii*) estimate the number of deaths, (*iii*) only consider binary outcome variables of *any* attack or deaths, and (*iv*) correct the data for reporting bias using Drakos' (2007) estimates. All corresponding results confirm our benchmark findings (see Section 5.3). Second, related to the number of sources employed by the GTD, the database is put together using articles from more than 160 countries and over 80 languages, which leads to an initial pool of over one million articles (see *GTD* Codebook, p. 7). This makes it less likely that attacks (and especially those resulting in fatalities) remain entirely undetected. Third, several studies analyzing the relationship between regime type and terrorism find no evidence of an underreporting bias (e.g., see Walsh and Piazza, 2010, Young and Dugan, 2011, or Piazza,

[9] An attack is categorized as transnational if either the perpetrator group does not belong to the country attacked, the nationality of the targets or victims do not belong to the country attacked, or the nationality of the perpetrators is different from that of the targets or victims. In case none of these criteria are met, the attack is categorized as a domestic attack. Nevertheless, our results are consistent when considering the unclassified attacks as domestic or transnational attacks (see appendix Table A1).

2013). In sum, although we cannot completely eliminate the possibility that our results are influenced by a possible reporting bias, the above mentioned reasons and the corresponding results of alternative estimations are reassuring and it remains unlikely that they would be *completely* explainable by a possible reporting bias.

4.1.2 Data on Information Flows

To measure the degree of information flows and the available CT in a given country and year, we employ the KOF index of information flows. This index represents one of the sub-indices of the KOF index of globalization, developed annually for 207 countries from 1970 to 2014 (Dreher, 2006, Dreher et al., 2008). Published by the KOF Swiss Economic Institute, the index ranges from zero to 100 and consists of three variables: The number of internet users, the share of households with a television set, and trade in newspapers as a percentage of GDP.[10] Thus, this index closely captures the concept of τ from our theoretical framework, assessing the degree of CT within a society that facilitates the flow of information. To facilitate the comparison of magnitudes in the upcoming regression analysis, we divide the index by 100, so it ranges between zero and one.

At this point, it is useful to consider the closest related studies when it comes to analyzing the 'publicity argument' with respect to terrorism. Several studies have employed binary indicators of press freedom to capture whether and how the existing media environment in a country can perhaps help terrorists gain publicity (Li, 2005, Sawyer, 2005, Chenoweth, 2010, and Asal and Hoffman, 2016). This argument focuses on the regulatory environment of a country – intuitively, if the press is not free to report on potential terrorist attacks, terrorists may be deterred from attacking for the same reasons we build our hypothesis on. However, our concept is broader in that the general degree of information flows in society may be able to affect the terrorists' decision. As such, the regulatory environment may well affect information flows, but the entire degree of information flows is not fully captured by press freedom alone. The

[10] Details on data collection and methodology for computing the index are available under http://globalization.kof.ethz.ch/.

corresponding measures of press freedom in this strand of research have been taken from the *Freedom of the Press* data (Freedom House, 2011) or from Van Belle's *Global Media Freedom* dataset (Whitten-Woodring and Van Belle, 2017). Indeed, these datasets either do not consider (Van Belle's measure) or under-represent (the *Freedom of the Press* data) modern channels of communication, such as internet usage.

Motivating our hypothesis, a large literature on communication studies has established that the availability of modern media channels not only improves communication and the flow of information, but may also drive political awareness and participation more effectively than traditional channels (Bakker and De Vreese, 2011, Valenzuela et al., 2012, Enjolras et al., 2013). For example, recognizing social media as an alternative to traditional media is necessary to understand the extent of mass mobilization, especially because social media targets different age groups and socio-economic classes (Enjolras et al., 2013). With respect to terrorism, Weimann (2006) documents that terrorists use the internet for raising funds, winning support, and recruiting followers, as well as planning and executing attacks. In short, our hypothesis here incorporates the comprehensive situation of a country when it comes to information flows via CT, rather than focusing on the regulatory environment alone.

To get a preliminary idea of the empirical relationship between CT and terrorism, Figure 3 visualizes two basic descriptive relationships. Panel A plots the share of internet users against the number of terrorist attacks in country-year observations, whereas Panel B displays the number of terrorist attacks against the KOF index of information flows. We observe a bell-shaped relationship in both graphs, as suggested by our theoretical framework. Although only of a descriptive nature, these simple comparisons are suggestive of a systematic relationship between information flows and terrorism and motivate our econometric analysis.

4.1.3 Control variables

To ensure that other, potentially confounding factors are not driving our estimations, we include a comprehensive set of control variables based on the existing cross-country literature. First, we consider characteristics associated with the political regime, following Li (2005), Piazza (2008a),

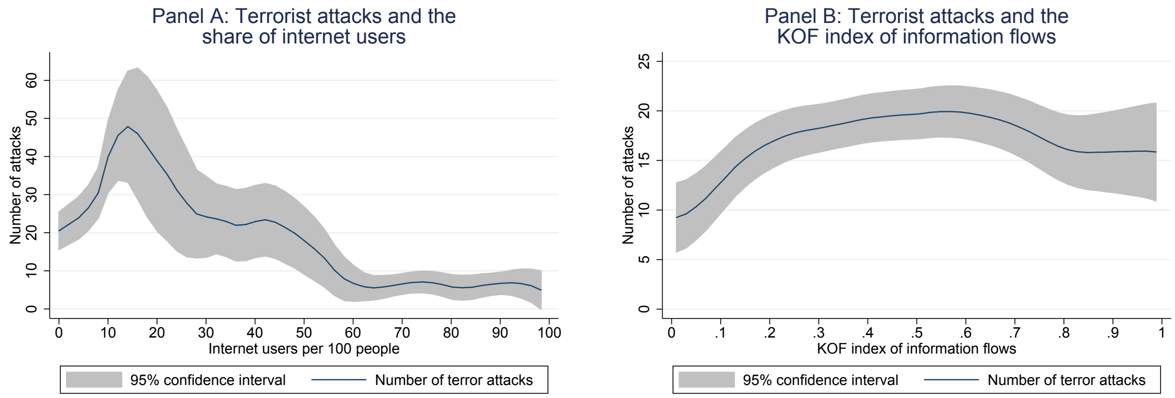

Figure 3: Information flows and terrorism. Both graphs employ a kernel-weighted local polynomial smoothing of country-year observations, displaying the corresponding 95 percent confidence interval.

Chenoweth (2012, 2013), and Gaibulloev et al. (2017), among others. Specifically, we include the *polity*2 variable from the Polity IV dataset to measure the degree of democratization (Marshall et al., 2017b). The index ranges from -10 to +10 with lower values indicating autocratic regimes and higher values referring to democracy. Since the literature suggests a non-linear relationship between regime type and terrorism, we also include the square of *polity*2 (Gaibulloev et al., 2017). To properly construct the squared relationship, we therefore first re-scale the *polity*2 indicator to range from zero to 20. Next, we incorporate a measure for regime durability via the *durable* score from the Polity IV dataset, since countries undergoing a regime change have been suggested to be more vulnerable to terrorism (Weinberg and Eubank, 1998, Wilson and Piazza, 2013).

Second, we control for GDP per capita and population size, accessing the World Development Indicators (see World Bank, 2016). Consistent with the existing literature, we apply the natural logarithm to both variables. Intuitively, while economic development can alleviate grievances of an opposition group, more substantial resources also increase the 'prize' of terrorism. With respect to transnational terrorism, higher economic development can also symbolize more attractive targets. Hence, a priori, the literature has produced somewhat mixed evidence as to *how* income levels are related to terrorism (e.g., see Blomberg and Hess, 2008, Piazza, 2013, or

Wilson and Piazza, 2013). Further, everything else equal, a larger population may be associated with more terror attacks due to difficulties associated with policing or simple scale arguments (e.g., see Li, 2005).

Third, we control for a country's involvement in conflicts by including data on interstate and internal armed conflicts, using data from Melander et al. (2016) and UCDP/ PRIO (2017). While internal armed conflict is expected to increase terrorism because arms are easier to access and a potentially vulnerable security situation, interstate armed conflict is associated with increased security at home and, thus, may reduce terrorism by increasing its costs (Li, 2005). In addition, following Piazza (2007, 2008b), Kis-Katos et al. (2011), and Wilson and Piazza (2013), we include a variable indicating state failure derived from the *Political Instability Task Force* (*PITF*, see Marshall et al., 2017a). Following Piazza (2008b), this variable is constructed as an aggregation of four types of state failures: Adverse regime changes, ethnic wars, geno/policides, and revolutionary wars. Further, we incorporate the *Composite Index of National Capability* (*CINC*, see Singer et al., 1972, and Singer, 1988) to capture a state's capacity for counterterrorism, following suggestions from Li (2005) and Gaibulloev et al. (2017), among others.

Finally, in order to account for unobserved characteristics along the country and time dimension, we employ country- and year-fixed effects. Specifically, a number of time-invariant country-specific drivers of terrorism have been suggested, all of which can be accounted for in a fixed-effects setting when using panel data. For instance, Abadie (2006) suggests country area, elevation, and fraction of tropical area as relevant predictors of terrorism. Collier and Hoeffler (2004) suggest that mountainous terrain and forests can provide safe havens for rebels, decreasing their probability of being caught, while Fearon and Laitin (2003) propose that noncontiguous territories favor potential rebels. Further, with respect to time-fixed effects, it is possible that large-scale global or regional developments can influence both terrorism and the degree of information flows at the same time. For instance, the Cold War era or the post-9/11 period imply global shocks that could well affect terrorism and perhaps information flows simultaneously (see Li, 2005, or Gaibulloev et al., 2017). Fixed effects will account for such developments.

Table 1: Summary Statistics of all variables.

Variable	Variable description	Obs.	Mean	Std. Dev.	Min	Max	Data source
Attacks	Total number of attacks in a country-year	9,849	15.92	99.95	0	3,925	Global Terrorism Database
Domestic Attacks	Total number of domestic attacks in a country-year	7,857	6.63	40.07	0	1,151	Global Terrorism Database
International Attacks	Total number of transnational attacks in a country-year	8,718	3.19	16.14	0	453	Global Terrorism Database
KOF index of information flows	An index of information flows ranging from 0 to 1 with higher values associated with larger flow of information	8,243	0.51	0.23	0.01	0.99	Dreher (2006), Dreher et al. (2008)
Polity2	(Polity2 score + 10)/20	6,801	11.23	7.37	0	20	Polity IV dataset (Marshall et al., 2017b)
Duration of regime	Log(regime durability score)	6,199	2.67	1.18	0	5.33	Polity IV dataset (Marshall et al., 2017b)
Interstate armed conflict (yes/no)	Interstate armed conflict	9,982	0.02	0.12	0	1	UCDP/PRIO Armed Conflict dataset (2017)
Internal armed conflict (yes/no)	Internal armed conflict	9,982	0.10	0.30	0	1	UCDP/PRIO Armed Conflict dataset (2017)
Political instability index	Index of state failure	9,982	0.42	1.39	0	14.00	PITF
Ln(GDP/capita)	Log of GDP per capita at constant 2005 prices in US dollars	7,472	8.26	1.52	4.75	11.89	UN Statistics
Ln(population size)	Log of total population	9,907	14.83	2.43	8.60	21.04	World Development Indicators
Composite Index of National Capability	Composite index of national capability (CINC)	7,244	0.01	0.02	0	0.22	National Material Capabilities (version 5.0) (Singer et al., 1972; Singer, 1988)

4.2 Methodology

Following the bulk of the literature, our empirical specification employs a negative binomial regression framework since the dependent variable represents a count variable (see Piazza, 2008b, Chenoweth, 2010, Walsh and Piazza, 2010, and Findley and Young, 2011; see Cameron and Trivedi, 2013, for a discussion about the underlying statistics). Alternatively, one could use a Poisson model that is specifically designed for predicting a nonnegative count variable. However, the data exhibit overdispersion and assuming independence between observations may not be valid, which generally speaks against a Poisson model (Cameron and Trivedi, 1998, Brandt et al., 2000). Further, some terrorism studies use a zero-inflated negative binomial regression framework, motivated by employing the Vuong test (Hoffman et al., 2013, Wilson and Piazza, 2013). However, both the zero-inflated negative binomial model and the Vuong test for testing its validity have recently been criticized (e.g., see Allison and Greene, 2012, Xie et al., 2013, Wilson, 2015, or Fisher et al., 2017). Nevertheless, our findings are consistent with either specification, as will be discussed in Section 5.3. Our main specification of a negative binomial regression framework for country i and year t becomes

$$Attacks_{it} = \alpha_0 + \alpha_1 \big(Info\,flows\big)_{it} + \alpha_2 \big(Info\,flows\big)^2_{it} + \boldsymbol{X}_{it}\alpha_3 + \lambda_i\alpha_4 + \gamma_t\alpha_5 + \delta_{it}, \qquad (5)$$

where we are interested in the coefficients α_1 and α_2. If our hypothesis was reflected in the empirical observations, we would expect α_1 to take on a positive and statistically meaningful value, whereas α_2 should turn negative, but also statistically relevant. Further, $\boldsymbol{X}_{it}$ constitutes the vector of control variables discussed in Section 4.1.3; λ_i represents country-fixed effects; γ_t includes year-fixed effects; and δ_{it} corresponds to the conventional error term.

Although we allow for nonlinearity in the KOF index in our main specification, we also test for a more flexible approach via a semi-parametric estimation. Figure A1 in the appendix Section A.4 documents that the corresponding results support a quadratic relationship between the number of terrorist attacks and information flows, thereby reassuring us about the functional form employed here.

5 Empirical Findings

5.1 Main Results

Table 2 presents our main results. The first column displays results from a univariate estimation, where we only use the KOF index of information flows in its linear form to predict the number of terror attacks. Interestingly, the respective coefficient is not statistically significant on any conventional levels with a t-value of 0.33 (equal to $\frac{0.329}{1.002}$). However, as soon as we introduce a squared term in column (2) to account for the suggested nonlinearity, information flows become a strong predictor of terrorism. In particular, the linear term turns positive and the squared term negative, indicating that information flows are first associated with more terrorism, but then decrease the number of attacks at higher levels of information flows. Toward the bottom of Table 2, we list the KOF value associated with the implied peak. In column (2), that peak corresponds to an intermediate KOF value of 0.54.

Columns (3) and (4) include our complete set of control variables, year-fixed effects, as well as country-fixed effects. Most importantly, the relationship between information flows and terrorism remains robust and the most complete estimation in column (4) produces statistical significance on the one percent level for both the linear and the squared term. The relationship is suggested to peak at a KOF value of 0.53. To provide a better idea of that range of information flows, it may be useful to consider the most recent KOF data. For instance, from 2010 to 2015, six countries (Afghanistan, India, Nigeria, Pakistan, the Philippines, and Yemen) account for 46 percent of all terror attacks; in all those countries, the KOF score of information flows ranges between 0.43 and 0.53. Of course, we are not suggesting that these countries are particularly prone to terrorism *only* because of an intermediate range of information flows, but our results suggest that CT may indeed contribute. In terms of magnitude, our results imply that if Sierra Leone in 2014 were to increase their KOF score by 10 percentage points, from 0.32 to 0.42 (to match that of Papua New Guinea, for example) while keeping everything else constant, we would expect the number of terrorist attacks to increase by 14 percent. However, considering an example beyond the suggested peak, if Brazil were to increase its KOF score from 0.70 (in

Table 2: Predicting the number of terror attacks, employing a negative binomial regression framework.

	(1)	(2)	(3)	(4)	(5) Domestic attacks only	(6) International attacks only
Dependent variable: # of terror attacks in country i and year t (mean = 15.92)						
KOF index of information flows	0.329	6.069***	9.288***	4.350***	5.436***	5.417***
	(1.002)	(2.348)	(1.228)	(0.448)	(0.696)	(0.570)
(KOF index of information flows)^2		-5.604**	-7.453***	-4.070***	-4.949***	-5.803***
		(2.820)	(1.062)	(0.406)	(0.665)	(0.505)
Polity2			0.223***	0.119***	0.157***	0.096***
			(0.078)	(0.022)	(0.033)	(0.029)
(Polity2)^2			-0.008**	-0.004***	-0.005***	-0.002*
			(0.004)	(0.001)	(0.001)	(0.001)
Standard controls[a]			yes	yes	yes	yes
Year-fixed effects			yes	yes	yes	yes
Country-fixed effects				yes	yes	yes
KOF score at maximum		0.54	0.62	0.53	0.54	0.46
# of countries	199	199	158	155	105	140
# of years	44	44	42	41	41	41
N	8,046	8,046	5,034	4,934	2,596	3,843

Notes: Standard errors are displayed in parentheses and clustered on the country level in columns (1) – (3). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Standard controls include variables measuring regime duration, interstate and internal armed conflict, the political instability index, the log of GDP per capita and population, as well as the Composite Index of National Capability.

2014) to the level of Sweden (KOF score of 0.80), we would expect the number of terror attacks to decrease by 16 percent.

Figure 4 visualizes the suggested relationship for the KOF index in Panel A and, as a comparison, for the degree of democracy in Panel B. Note that we use the same scale on the y-axis to facilitate comparing magnitudes. In Panel A, terror attacks are increased by almost 120 percent at a value of $KOF = 0.53$, relative to a hypothetical KOF score of zero. Panel B then serves as a reference point, visualizing our predicted effect of democracy, as suggested by Chenoweth (2013) and Gaibulloev et al. (2017). Consistent with their findings, democratization is also suggested to follow an inverted U-shape in its relationship with terrorism, but the underlying magnitudes are, in fact, smaller. Here, terrorism is suggested to be most severe for a $polity2$ score of 14.48 – but at this peak, we should only expect an increase of 85 percent, relative to a complete autocracy (a $polity2$ score of zero). This comparison highlights that information flows may not only be a statistically relevant predictor of terrorism, but also a quantitatively sizeable one.

Panel A
KOF index of information flows

Panel B
Polity IV

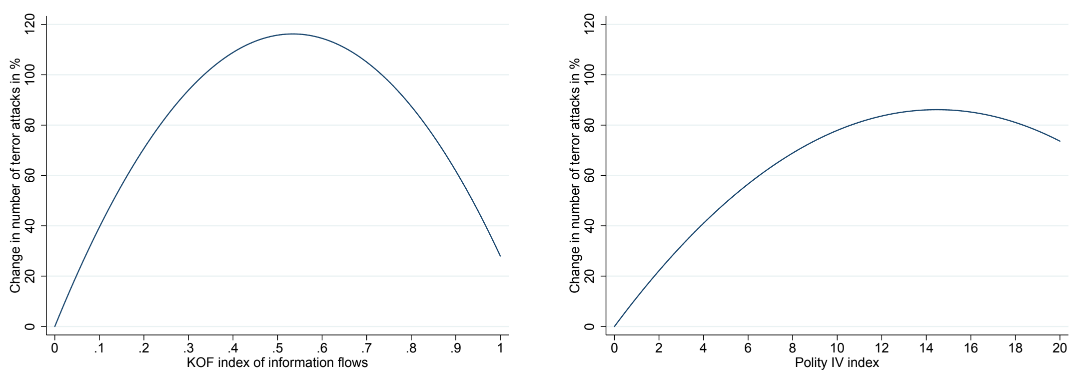

Figure 4: Visualizing regression results from column (4) in Table 2.

Finally, columns (5) and (6) replicate our most complete estimation, but separately consider domestic and transnational terrorism. It is interesting to see that the respective results are consistent with our benchmark finding from column (4). The suggested peak value of information flows again occurs at intermediate ranges of the KOF index with values of 0.54 and 0.46. In the upcoming section, we now turn to alternative specifications, extensions, and placebo regressions to verify whether the derived results from Table 2 remain consistent. In all of these estimations, we will consider the results displayed in column (4) of Table 2 as our benchmark regression.

5.2 Robustness Checks

First, one concern with interpreting our results lies in the potential correlation between the state of CT in a country and its level of development.[11] Specifically, the inverted u-shaped relationship obtained in Panel A of Figure 4 may be driven by development-related aspects. Although our main estimation controls for GDP per capita, we also analyze individual subsamples of poor, lower-middle income, upper-middle income, and rich countries by dividing our sample by quartiles of GDP per capita (while still controlling for income levels). In another estimation, we control for a squared term of GDP per capita, following the research developed by Enders and Hoover (2012) and Enders et al. (2016). The corresponding results confirm our baseline findings of a nonlinear and strongly statistically relevant link between the KOF index and the number of terror attacks (results are available in Table A2).

Second, Table 3 displays results from 12 alternative estimations. In columns (1) – (3), we consider other functional forms to predict terrorist attacks. Specifically, we display results from (i) calculating bootstrapped standard errors in our familiar negative binomial regression framework (using 100 replications), (ii) applying a Poisson regression framework, and (iii) employing a standard OLS regression. In columns (4) –(9), we further test whether government size, press freedom, political rights, civil liberties, democratic participation, executive constraints, or inequality can explain away the inverted U-shaped relationship between information flows and terrorism. All of these variables have been proposed as meaningful drivers of terrorism before.[12]

[11] The correlation coefficient between the KOF index and GDP per capita reaches a value of 0.76.

[12] Government size has been suggested by several studies as a potential determinant of terrorism (e.g., see Kirk, 1983, Freytag et al., 2011, and Krieger and Meierrieks, 2011). We use general government final consumption expenditure as a percentage of GDP from the *World Bank* as an indicator of government size. In column (5), we follow the existing literature on the importance of press freedom in explaining terrorism (Hoffman et al., 2013, Asal and Hoffman, 2016, and Bakker et al., 2016) and include a binary variable for countries that are categorized as free in the *Freedom of the Press* data (Freedom House, 2011). In columns (6)–(8) we incorporate additional institutional controls that are shown relevant for explaining terrorism in the literature (Li, 2005, Young and Dugan, 2011, and Hoffman et al., 2013). Data on political rights and civil liberties are taken from Freedom House

In column (10), we control for past incidences of terrorism, following suggestions from Hoffman et al. (2013) and Young and Dugan (2011). Next, we predict the number of fatalities in column (11) instead of the number of attacks. Finally, the regression results displayed in column (12) predict the *onset* of terrorism, following the spirit of the conflict literature, where incidence, i.e., the intensity, are distinguished from beginning conflict where no violence occurred in the year prior (e.g., see Collier and Hoeffler, 1998, Fearon and Laitin, 2003, Collier and Hoeffler, 2004, Miguel et al., 2004, or Blattman and Miguel, 2010). Thus, onset is coded as equal to one if the country experienced *any* terrorism in the present year, but no terrorism in the previous year. However, the nonlinear influence of the KOF prevails throughout all additional estimations in Table 3.

5.3 Accounting for Reporting Bias

Third, a potential reporting bias could confound our analysis. If terrorist attacks were systematically under-reported in countries with little press freedom, our results could be biased in that the suggested relationship would not follow an inverted U-shape, but rather could be a linear negative relationship. To test for that possibility, we conduct a series of additional estimations with the results displayed in Table 4. In column (1), we display results from re-estimating our main regression, but only employ those country-year observations where the press is rated to be free or partly free by the *Freedom of the Press* indicator. The corresponding results confirm a nonlinear relationship. Thus, those countries where we would be most concerned about a potential reporting bias are not driving our results.

In column (2), we return to the full sample and predict whether the country has experienced *any* terror attacks in the given year. Intuitively, although a regime may be able to hide *some* terror attacks, we propose that it would be difficult to hide if *any* terrorism was occurring. Estimating this binary outcome variable via a *logit* regression again confirms the suggested

(2011), whereas we access Vanhanen and Lundell's (2014) polyarchy dataset to measure democratic participation. Information about executive constraints is taken from the Polity IV dataset (Marshall et al., 2017b). Information on the Gini index as a measure of income inequality comes from Solt (2016) (see Li, 2005, and Piazza, 2013 on the importance of income distribution for terrorism).

Table 3: Displaying results from various robustness checks, building on the main specification of column (4) in Table 2.

Estimation Method:	NBREG[a]	Poisson	OLS	NBREG								Logit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Attacks										Deaths	Terrorism onset[c]
KOF index	4.350***	2.231***	123.180***	4.594***	4.274***	3.976***	4.285***	4.483***	5.020***	4.309***	6.276***	6.833***
	(1.041)	(0.125)	(24.979)	(0.500)	(0.481)	(0.459)	(0.458)	(0.446)	(0.453)	(0.453)	(0.567)	(2.152)
$(KOF \text{ index})^2$	-4.070***		-59.016***	-4.013***	-3.805***	-3.690***	-3.855***	-4.322***	-4.772***	-3.850***	-7.613***	
	(0.864)		(21.883)	(0.440)	(0.424)	(0.416)	(0.419)	(0.404)	(0.410)	(0.391)	(1.854)	
Additional control variables:				Government size	Press freedom	Political rights	Civil liberties	Democratic participation; Executive constraints	Gini index	Attacks_{t-1}		
Standard controls[b]	yes	yes	yes	yes	yes	yes	yes	yes[c]	yes	yes	yes	yes
Year-fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country-fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
# of countries	155	155	158	158	153	155	155	154	155	155	155	146
# of years	41	41	42	42	33	32	38	38	41	41	39	41
N	4,934	4,934	5,034	3,923	4,123	4,634	4,619	4,933	4,934	4,725	4,688	2,516

Notes: Standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Specification (1) reports bootstrapped (100 rep) standard errors while specification (2) reports results for Poisson regression. [b]Standard controls include Polity2 and its square, duration of regime, interstate and internal armed conflict, political instability index, the logarithm of GDP per capita and population size, as well as the Composite Index of National Capability. [c]Specification (8) does not include Polity2 and its square, following Li (2005) and Chenoweth (2010).

Table 4: Displaying results from further robustness checks to address concerns about reporting bias.

	(1) Excluding non-free press	(2) Attack (yes/no)	(3) Deaths (yes/no)	(4) Excluding non-fatal attacks	(5) Zero-inflated NBREG	(6) Drakos and Gofa correction
KOF index	4.580***	10.648***	3.353***	11.652***	7.737***	3.117***
	(0.628)	(1.345)	(0.523)	(1.413)	(0.629)	(0.431)
(*KOF* index)^2	-3.730***	-10.692***	-2.790***	-11.189***	-5.741***	-2.594***
	(0.518)	(1.174)	(0.492)	(1.272)	(0.586)	(0.389)
Standard controls[a]	yes	yes	yes	yes	yes	yes
Year-fixed effects	yes	yes	yes	yes	yes	yes
Country-fixed effects	yes	yes	yes	yes	yes	yes
# of countries	124	146	136	143	155	152
# of years	33	41	41	41	41	41
N	2,663	4,653	1,619	4,622	5,034	2,435

Notes: Standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Standard controls include *polity*2 (re-scaled to range from zero to 20) and its square, regime duration, interstate and internal armed conflicts, the political instability index, the natural logarithm of GDP per capita and population size, as well as the Composite Index of National Capability. Specifications (2) and (3) employ a conditional logistic model while specifications (2), (4), and (5) use a negative binomial regression framework.

nonlinearity. Next, following Young and Dugan (2011), we count only those attacks in which at least one person was killed since it appears more difficult to completely censor news about fatal attacks, even in countries where information flows remain restricted. In column (4), using the same logic, we construct a binary indicator that captures whether the country suffered any deaths from terrorism in the given year. In column (5), we employ a zero-inflated negative binomial regression framework, which has been suggested to alleviate concerns about reporting bias (Lai, 2003; Drakos and Gofas, 2006b). Finally, we use the estimates provided by Drakos (2007) in their calculation of underreporting biases. Specifically, Drakos (2007) suggest an underreporting bias of 18 percent for countries featuring a partially free press and 21 percent for countries that are rated as not having a free press. Thus, in column (6), we consider only those observations with at least one attack and multiply the number of attacks by 1.18 and 1.21 for partly free and non-free countries, respectively, following the *Freedom of the Press* data (Freedom House, 2011).

Overall, the results displayed in Table 4 are encouraging in that none of the corresponding robustness checks would give us an indication that our results are systematically explainable by a potential reporting bias. Nonetheless, we can of course not completely eliminate that possibility and all interpretations of our findings should keep this in mind.

5.4 Placebo Regressions

In our final set of additional estimations, we now turn to placebo regressions with the corresponding results displayed in Table 5. As our hypothesis related to CT is specific to terrorism and the underlying importance of information flows for terrorism, we should not observe a non-linear relationship between information flows and other types of organized violence. In columns (1) – (3), we predict whether the country experienced an internal (or internationalized internal) conflict or war.[13] (Note that sample sizes are decreased solely because many countries have not experienced statistical variation in the dependent variable.) However, we do not observe the

[13] In the corresponding literature, a civil conflict is defined as drawing at least 25 battle-related deaths in the given year, whereas a civil war would draw at least 1,000 battle-related deaths (also see Blattman and Miguel, 2010). We access data from UCDP/ PRIO (2017) to calculate the respective binary indicators on the country-year level.

same nonlinearity between the *KOF* index of information flows and these forms of organized violence.

Table 5: Displaying results from placebo regressions, using the full sample in columns (1) – (3), (6), and (7). In columns (4) and (5), we use those country-year observations that show data for homicide rates.

Estimation method:	Logit			OLS		NBREG	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Internal conflict	Internal war	Internal conflict or war	Homicide rate	Attacks		
KOF index	2.741 (1.861)	4.410 (4.559)	3.001 (2.381)	-8.142 (8.675)	248.163*** (89.420)	4.235*** (0.462)	3.879*** (0.599)
(*KOF* index)^2	-6.491*** (1.879)	-3.610 (5.446)	-6.473*** (2.401)	11.450* (6.827)	-202.751*** (70.374)	-4.122*** (0.421)	-3.796*** (0.592)
KOF index of political globalization						-0.237 (0.716)	
(*KOF* index of political globalization)^2						0.564 (0.581)	
KOF globalization index							1.762 (1.093)
(*KOF* globalization index)^2							-0.919 (0.938)
Standard controls[a]	yes	yes	yes	yes	yes	yes	yes
Year-fixed effects	yes	yes	yes	yes	yes	yes	yes
Country-fixed effects	yes	yes	yes	yes	yes	yes	yes
# of countries	73	33	69	156	156	155	155
# of years	43	43	43	18	18	42	42
N	2,464	1,114	2,302	1,627	1,627	4,934	4,934

Notes: Standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Standard controls include *polity*2 (re-scaled to range from zero to 20) and its square, regime duration, interstate and internal armed conflicts, the political instability index, the natural logarithm of GDP per capita and population size, as well as the Composite Index of National Capability.

Further, in column (4) we predict the rate of intentional homicides (per 100,000 people), using data from the World Bank (2016). Here again, we do not observe a nonlinear link that would be consistent with our hypothesis. In column (5), we document that this finding is not driven by the substantially reduced sample size for which the homicide rate is available by re-estimating our main estimation with only those observations where the homicide rate is available. These results further indicate that the nonlinear effect from information flows is specific to terrorism and does not emerge for other forms of major violence.

Finally, columns (6) and (7) focus on the KOF index of information flows. As our argument is specific to information flows, we would predict that other indices of globalization do not follow the nonlinear patter in describing terrorism. Indeed, when including the KOF indices for political globalization and the overall KOF index of globalization, we derive statistically insignificant results – however, the KOF index of information flows remains a meaningful predictor in its original nonlinear form.

6 Conclusion

This paper proposes a systematic relationship between the existing degree of communications technology and terrorism. We begin by introducing a simple theoretical framework in the spirit of Becker (1968), where a representative profit-maximizing agent allocates their time between terrorism and participating in the labor market. The corresponding predictions suggest a nonlinear link between communications technology and terrorism: As communications technology improves, facilitating the flow of information in society, the optimal time devoted to terrorism first increases, but then decreases. In particular, monitoring and apprehending potential terrorists becomes easier for law enforcement and, in turn, returns from the labor market become relatively more attractive.

We then test these predictions, studying up to 199 countries from 1970 to 2014. The suggested nonlinearity emerges throughout all of our specifications, even after controlling for a comprehensive list of potentially confounding covariates, as well as country- and time-fixed effects. Indeed, a rise in information flows is systematically associated with an increase in terrorism at first, but after peaking at an intermediate range of information flows, the relationship turns negative. That peak corresponds to Afghanistan, India, Nigeria, Pakistan, the Philippines, and Yemen in 2014, for example – countries which were some of the most terror-prone nations at the time, accounting for 46 percent of all terrorist attacks worldwide. Alternative econometric specifications produce consistent findings and it appears unlikely that a potential reporting bias in measuring terrorist attacks can fully explain our findings.

Overall, we hope this study helps to better explain when and why terrorism may arise. As a society develops communications technologies, such as currently the internet and specifically social media, it may become vulnerable to terrorism at first. However, as information continues to flow better, terrorism may become less attractive. These results may also help us to predict what may happen after large shocks in terms of communications technology, such as the widespread distribution of television, smartphones, the internet, or social media. At first, such shocks may indeed facilitate terrorism, and policymakers may benefit from understanding this possibility in advance. Future research may be able to better distinguish between the introduction of different types of communications technology, as well as more micro-founded analyses. We hope that our paper provides a starting point to inspire further inquiry into the systematic link between communications technology and terrorism.

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A Appendices

A.1 An Alternative Specification of the Profit Function

To separate out the marginal effects of β and τ, let us assume that the profit function of the representative agent takes the following form:

$$\pi(\beta) = \big(1-\tau\big)\beta^{\delta}\tau^{\alpha} + (1-\beta)w, \tag{A1}$$

such that $0 < \alpha < 1$, $0 \leq \tau \leq 1$ and $\delta > 0$. Maximizing π with respect to β yields the optimal time devoted to terrorism β^* with

$$\beta^* = \left[\frac{\delta[1-\tau]\tau^{\alpha}}{w}\right]^{\frac{1}{1-\delta}}. \tag{A2}$$

Comparative statics along the line of τ give us the change in the optimal time devoted to terrorism in response to a change in τ with the peak in β^* associated with τ^* such that

$$\tau^* = \frac{\alpha}{1+\alpha}. \tag{A3}$$

A.2 Proof of τ^* Constituting a Maximum, not a Minimum

Since $\frac{\partial\beta^*}{\partial\tau} = \frac{1}{1-\alpha}(\frac{\alpha\tau^{\alpha}(1-\tau)}{w})^{\frac{\alpha}{1-\alpha}}(\frac{-\alpha\tau^{\alpha}}{w} + \frac{(1-\tau)\alpha^2\tau^{\alpha-1}}{w})$, , we can take another derivative with respect to τ and obtain $\frac{\partial^2\beta^*}{\partial\tau^2} = (\frac{1}{1-\alpha})(\frac{1}{w})^{\frac{1}{1-\alpha}}[(\frac{\alpha}{1-\alpha})(\alpha\tau^{\alpha}(1-\tau))^{\frac{2\alpha-1}{1-\alpha}}(-\alpha\tau^{\alpha} + (1-\tau)\alpha^2\tau^{\alpha-1})((\alpha-1)(1-\tau)\alpha^2\tau^{\alpha-2} - \alpha^2\tau^{\alpha-1}]$. This expression is strictly negative since $(\alpha-1)(1-\tau)\alpha^2\tau^{\alpha-2} < \alpha^2\tau^{\alpha-1}$ (given $\alpha < 1$).

A.3 Alternative Classification of Attacks in the GTD

Table A1: Predicting the number of terror attacks, employing an alternative classification of attacks into domestic and international.

	(1) Domestic (excluding unclassified)	(2) Domestic (including unclassified)	(3) International (excluding unclassified)	(4) International (including unclassified)
KOF index of information flows	5.436***	3.931***	5.417***	4.293***
	(0.696)	(0.503)	(0.570)	(0.456)
(*KOF* index of information flows)^2	-4.949***	-3.374***	-5.803***	-4.398***
	(0.665)	(0.456)	(0.505)	(0.414)
Standard controls[a]	yes	yes	yes	yes
Year-fixed effects	yes	yes	yes	yes
Country-fixed effects	yes	yes	yes	yes
# of countries	105	152	140	154
# of years	41	41	41	41
N	2,596	4,468	3,843	4,822

Notes: Standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Standard controls include Polity2 and its square, duration of regime, interstate and internal armed conflict, political instability index, the logarithm of GDP per capita and population size, as well as the Composite Index of National Capability.

A.4 Results from a Semi-parametric Regression Model

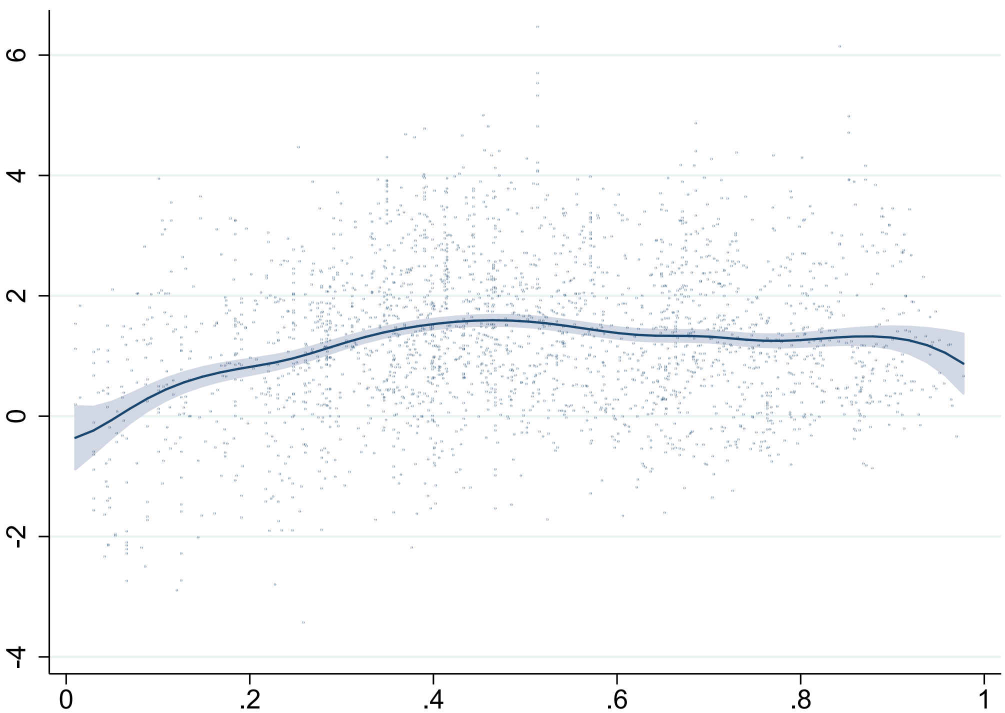

Figure A1: Semiparametric Effects: The logarithm of number of terrorist attacks and the *KOF* index of information flows when controlling for the familiar set of covariates and time-fixed effects (see column 4 of Table 2), employing the *semipar* Stata command (Robinson et al., 1988).

A.5 Exploring the Role of Income Levels

Table A2: Predicting the number of terror attacks for different subsamples of countries and alternative control variables. Specifications (1) – (4) depict results for sub-samples of poor, lower-middle income, upper-middle income, and rich countries, respectively, classified on the basis of GDP per capita quartiles.

	(1)	(2)	(3)	(4)	(5)
Dependent variable: # of terror attacks in country i and year t (mean = 15.92)					
KOF index of information flows	5.083***	5.548***	5.225***	3.684**	5.893***
	(1.342)	(0.816)	(0.596)	(1.782)	(0.514)
(*KOF* index of information flows)^2	-4.625**	-5.453***	-4.870***	-2.636*	-5.591***
	(1.939)	(0.960)	(0.608)	(1.485)	(0.475)
(Ln(GDP/capita))^2					0.093***
					(0.015)
Standard controls[a]	yes	yes	yes	yes	yes
Year-fixed effects	yes	yes	yes	yes	yes
Country-fixed effects	yes	yes	yes	yes	yes
# of countries	58	96	127	40	155
# of years	41	41	41	41	41
N	1,386	2,574	3,713	1,205	4,934

Notes: Standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Standard controls include Polity2 and its square, duration of regime, interstate and internal armed conflict, political instability index, the logarithm of GDP per capita and population size, as well as the Composite Index of National Capability.