How Terrorism Spreads: Information, Emulation, and the Spatial Diffusion of Ethnic and Ethnoreligious Terrorism

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Abstract

Previous research on the causes of terrorism has tended to focus on domestic determinants. Although such a closed-polity approach can be helpful to understand many causes of terrorism, existing research has generally had little to say about diffusion as a determinant of domestic terrorism or the conditions under which terrorist tactics can spread from one group to others. This study identifies theoretically and tests empirically the mechanisms of diffusion of ethnonationalist and ethno-religious domestic terrorism. The adoption of terrorist tactics on the part of ethnic and ethno-religious groups often results from social emulation between politically similar (e.g. politically excluded) and geographically proximate groups as well as groups connected by preexisting networks (e.g. same ethnic kin-diaspora, or religious ties). The hypotheses are tested on a new dataset of ethnonationalist and ethno-religious terrorist organizations from 1970 to 2009 using spatial statistics and Bayesian spatial econometric models. The results provide strong support for the hypothesized mechanisms leading to the diffusion of terrorist tactics and suggest that learning and emulation – in addition to domestic and contextual factor – influence dissidents' tactic choice.

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Introduction

The so-called Arab Spring and the uprisings and revolutions in North Africa and the Middle East have sparked a renewed interest in the diffusion of violent as well as non-violent conflict tactics and under what conditions groups can draw inspirations from political actions abroad. In Syria, terrorist tactics – especially car bombings, suicide attacks, and unconventional attacks against government targets – have been adopted by the Sunni Islamist organization Jabhat al-Nusra. These resemble the tactics previously adopted by other Sunni groups in the region, especially al-Qaida in Iraq, even though the leadership of al-Nusra has denied any alliance with the recently established Islamic State (IS) in Iraq.[1] Recent events of domestic terrorism such as the January 2015 attack against the French satirical newspaper Charlie Hebdo, in which venue, victims, and perpetrators all belonged to the same country, do not appear to be rooted solely in domestic grievances of disenfranchised individuals. In fact, these terrorist attacks cannot be fully understood without taking into account transnational sources of radicalization and recruitment and how ongoing conflicts in other regions of the world, especially the Middle East and North Africa, spur sympathies toward terrorism as an alternative political project or an easy route for revenge for other similar groups who identify with those conflicts. These examples, among others, suggest how terrorist events taking place in one country or involving specific groups within a country can inspire other groups in the same or neighbouring region to adopt similar tactics and ultimately create incentives for domestic political mobilization.

How does terrorism diffuse? Although commonly treated as independent in many studies, terrorist events are likely to be both temporally and spatially dependent. They are temporally dependent in the sense that previous successful attacks increase the likelihood of future attacks (Neumayer and Plümper, 2010). But terrorist organizations are also unlikely

[1] See http://www.bbc.co.uk/news/world-middle-east-18048033

to act in complete isolation from each other. Groups often have similar goals, or compete with each other for limited resources and support. Moreover, terrorist behavior is highly imitable(Midlarsky, Crenshaw and Yoshida, 1980). Terrorist acts tend to be spectacular, dramatic, highly symbolic, and this type of violence is in its essence newsworthy and attracts international publicity. As a tactic, terrorism is also relatively easy to copy and often less costly than conventional warfare.

This article analyzes the specific mechanisms through which terrorist tactics diffuse between ethnic groups. It provides the first systematic group-level analysis of the diffusion of domestic terrorism, with a particular focus on ethno-nationalist and ethno-religious terrorism.[2] I argue that the decision to adopt terrorist tactics is not simply a consequence of a group's domestic situation: it is also shaped by social emulation between politically similar and geographically proximate ethnic groups. Adopters of a tactic define themselves as similar to the transmitters to justify using them as a model for their own actions and the tactic in question as relevant to their situation. Structural similarity between groups, especially shared political marginalization or exclusion, can facilitate mutual identification while proximity and ethnic networks influence the frequency of communication and the direct nature of interactions between groups thus facilitating not only the spread of information on tactics but also the acquisition of expertise in their use which further increases organizational effectiveness. These mechanisms together lead to imitative behavior and to the consequent diffusion of terrorist tactics. This provides an actor-level mechanism of diffusion based on the interaction between political similarity and geographic proximity of potential adopters and transmitters[3], as well as gating factors which influence the degree of group responsiveness to demonstration effects.

[2]Ethnonationalist and ethnoreligious terrorism dominate global terrorism events, at least for attacks where we can identify the perpetrators (based on the new dataset described later).

[3]Geographic proximity, as defined in this paper, does not necessarily entail direct contiguity of ethnic group settlement.

Group-level analyses of terrorism are relatively rare due to the lack of available data. Studying the diffusion of terrorist tactics between ethnic groups faces an additional challenge in identifying the relevant populations from which terrorist organizations could emerge, as a consequence of learning and emulation from groups perceived as peers, as opposed to focusing only on organizations which already use terrorism. I introduce a new dataset of ethnic and ethno-religious terrorism linking organizations in the Global Terrorism Database (START) to ethnic groups in the Ethnic Power Relations database (Cederman, Min and Wimmer, 2010). Using spatial data on the geographic distance between ethnic group settlements and non-spatial data on their political status I generate measures of connectivity between all politically relevant ethnic groups between 1970 and 2009 based on their degree of political similarity and spatial proximity. I then examine the effect of previous adoption of terrorism by an ethnic group on the likelihood that other connected ethnic groups in the same and other countries resort to terrorism and find a strong positive effect. The results from a spatial econometric model further suggest that indirect effects, or spatial feedbacks, reflecting tactic diffusion are at least as important as the direct effect of group characteristics and domestic motivations for explaining the adoption of terrorist tactics.

By focusing on specific actor-level mechanisms of diffusion this study demonstrates empirically that domestic terrorism is not a purely domestic phenomenon, rooted in the individual characteristics of groups or countries, and that groups learn and emulate each other's tactics. Moreover, while geographic proximity alone is insufficient to account for diffusion and operates in conjunction with shared political marginalisation and pre-existing ethnic networks, a degree of spatial proximity can provide organizations with a competitive advantage for the adoption of terrorist tactics relative to purely non spatial mechanisms based on media effects. While research on ethnic conflict diffusion highlights the role of trans-border ethnic kin (e.g. Buhaug and Gleditsch, 2008; Forsberg, 2014), this study argues that shared kin membership is only part of a more general mechanism of terrorism diffusion and that tactical emulation can occur even between organizations belonging to different kin groups. This provides a more unified framework to explain instances of sub-national as well as transnational tactic diffusion. This study also contributes to existing literature on the causes and geography of terrorism by identifying theoretically and testing empirically the mechanisms of diffusion of ethnonationalist and ethnoreligious domestic terrorism. There is evidence that transnational and domestic terrorist events tend to be spatially clustered (e.g. Braithwaite and Li, 2007; Neumayer and Plümper, 2010; Nemeth, Mauslein and Stapley, 2014). However, geographic concentrations may be due to several reasons and not necessarily represent the outcome of a diffusion process (Galton, 1889). Existing studies have identified the existence of terrorism hot-spots and spatial dependence at the country level but unfortunately they do not provide a comprehensive theory on the mechanisms of terrorism diffusion or assess the relevance of competing mechanisms. Additionally, these studies only consider transnational terrorism[4], which constitutes a minority of global terrorism (Enders, Sandler and Gaibulloev, 2011; Sandler, 2014), and we know very little about the diffusion of domestic terrorism.[5] This is particularly unfortunate since external factors affecting the risk of domestic terrorism could make analyses of domestic factors that look at actors in isolation yield potentially misleading results about relevant causes of domestic terrorism and incomplete prescriptions for counterterrorism efforts. In this article, I develop a general actor-level theory of the diffusion of terrorism, applied specifically to ethno-nationalist terrorism.

This article proceeds as follows: after a review of extant research on the geography of terrorism and on conflict diffusion, I introduce a general actor-level theory of diffusion. The theory is then applied to the case of ethnonationalist terrorism in the following section, and

[4]Nemeth, Mauslein and Stapley (2014) examine the local geography of domestic terrorism but do not specifically focus on diffusion processes

[5]Global terrorism comes in two essential variants: domestic and transnational. Domestic terrorism is homegrown in that the venue, target, and perpetrators, all belong to the same country (Enders and Sandler, 2008). Conversely, transnational terrorism involves more than a single country, either through its victims, targets, or perpetrators (Enders and Sandler, 2008). A complete definition of terrorism is provided in the next section.

a diffusion mechanism is specified together with the hypotheses. The remaining sections present the data and methodology, discuss the empirical results, and suggest avenues for future research.

The Spatial Clustering of Terrorism and Ethnic Conflicts

Terrorism can be defined as the "deliberate creation and exploitation of fear through violence or the threat of violence" by non-state actors "in the pursuit of political change" (p.60 Hoffman, 2006; Enders and Sandler, 2012). It is a tactic of indirect targeting which operates through the intimidation of a larger audience beyond the immediate victims or physical targets. Research on terrorism has grown considerably over the past twenty years, and especially since the 9/11 attacks. However, existing research has tended to treat groups and attacks as independent and paid little attention to the possibility of terrorism diffusion from other countries or organizations as an additional determinant of domestic terrorism. It is clear from mapping the distribution of terrorism that terrorist incidents cluster in certain areas and are relatively rare in others.[6] In 2011, terrorist attacks in just five countries – Iraq, Pakistan, India, Afghanistan, and Russia – accounted for seventy per cent of incidents worldwide (GTD, 2013).[7] Geographic concentrations of terrorism are not immutable and often change over time, possibly reflecting different waves of terrorism. Clearly, the existence of spatio-temporal clusters *per se* does not provide evidence of terrorism contagion from one country or organization to others, and there may be other plausible reasons for the observed clustering. Nonetheless, their existence prompts questions about the relative

[6] See maps reported in the appendix.

[7] Moreover, nine out of the twenty most active terrorist organizations in 2011 are al-Qaida linked groups. For a full list see http://www.start.umd.edu/start/announcements/announcement.asp?id=424.

effect of domestic vs. regional or neighborhood factors as determinants of both domestic and transnational terrorism.[8]

The question of why we observe spatial clusters of terrorism has been generally overlooked in the literature, with few notable exceptions (Midlarsky, Crenshaw and Yoshida, 1980; Braithwaite and Li, 2007; Neumayer and Plümper, 2010; Nemeth, Mauslein and Stapley, 2014). A pioneering study by Midlarsky, Crenshaw and Yoshida (1980) finds that the diplomatic status of a country in which terrorism occurs influences the diffusion of transnational terrorism to other countries. Braithwaite and Li (2007) use local spatial statistics to identify transnational terrorism hot-spots and demonstrate countries in a terrorism hot-spot location are more likely to see future transnational terrorist attacks. This study is important in testing for spatial clusters of transnational terrorism and their effects, but it remains unclear what generates these clusters and whether this is due for instance to common exposure or interdependence between terrorist organizations. Based on Samuel Huntington's theory on the clash of civilizations, Neumayer and Plümper (2010) find that the different civilizations of origin and target country shape patterns of terrorism contagion. Finally, a number of studies introduce regional dummies to control for spatial heterogeneity, or the fact that some regions experience more terrorism, possibly due to unobserved factors (e.g. Li and Schaub, 2004; Savun and Phillips, 2009). Such control variable approaches, however, do little to explain the observed clustering and include very large regions, often entire continents (such as America, Africa, Asia, Europe). Moreover, this method implicitly assumes uniformity across countries in a region, which runs counter to the considerable variation in terrorist activities within these regions (for a comprehensive discussion see Braithwaite and Li, 2007). Findley and Young (2011) instead control for the effect of terrorism in neighboring

[8]Diffusion processes may be mediated by generic geographic proximity (non-actor specific), so that terrorism in one country is likely to spill over to neighboring countries, or by some kind of similarity between actors which does not necessarily require geographic proximity as it is often based on emulation of a self-identified peer nation or group. The latter phenomenon is generally known as "structural equivalence" (Simmons, Dobbin and Garrett, 2008).

countries.

To sum up, existing research on the geography of terrorism has been mainly empirical, focused on testing spatial dependence and clustering, but has not offered a comprehensive theoretical discussion on the mechanisms of diffusion or assessed the relevance of competing mechanisms. Moreover, existing studies generally focus on transnational terrorism, which constitutes a small share of global terrorism, and have less to provide on the diffusion of domestic terrorism. A recent study by Horowitz (2010) analyzes the diffusion of suicide tactics among terrorist organizations and identifies linkages with al-Qaida, together with organizational age, as relevant explanations for the adoption of this tactical innovation. The focus on specific organizations and their respective linkages highlights the importance of an agency-oriented approach. Yet, it remains a major challenge to identify the populations from which terrorist organizations can emerge as a consequence of learning and emulation from other groups, as opposed to the smaller set of groups that have already mobilized through terrorism. Moreover, not all types of terrorism may be equally likely to spread, or do so following the same mechanism or process. Further disaggregation is needed, for instance according to group goals and ideology, and especially in the case of domestic terrorism.

Studies of civil wars and ethnic conflicts have also investigated conflict contagion. This literature does not specifically focus on the tactics that groups adopt but mainly on civil war onsets. In this regard, geographic distance stands out as an important factor, as diffusion is expected to occur between neighboring or proximate countries.[9] At the same time, however, not all conflicts are equally likely to spread across countries and, more importantly, not all neighboring countries and groups are likely to be affected (e.g. Braithwaite, 2010; Metternich, Minhas and Ward, 2015). Buhaug and Gleditsch (2008) show that conflict contagion predominantly occurs within separatist conflicts, and that transnational ethnic ties

[9] Although recent research (Weidmann, 2015) argues that media effects, in addition to geographic proximity, can facilitate the diffusion of ethnic civil war.

to a neighboring conflict area increase the likelihood of conflict onset. However, it remains unclear whether the kin group that arguably could push other group members into violent behavior must experience conflict itself, or whether its mere presence, regardless of behavior, suffices to increase expected opportunities for domestic conflict (Forsberg, 2014), for instance when a neighbouring kin group can provide safe havens or material and logistical support to an insurgency (Cederman et al., 2013; Gleditsch, 2007; Salehyan, 2007). Moreover, many ethnic groups which have adopted terrorist tactics are not involved in civil wars and vice versa. Therefore it remains unclear whether and to what extent diffusion processes influence ethnic organizations' choice of specific tactics both within and outside civil war.

In addition, it is often argued that shared ethnic kin constitutes a key linkage creating either external opportunities for domestic conflict or leading to demonstration effects (e.g. Salehyan and Gleditsch, 2006; Gleditsch, 2007; Buhaug and Gleditsch, 2008; Cederman et al., 2013; Forsberg, 2014). However, looking only at actors and conflicts across borders overlooks subnational diffusion of tactics between ethnic groups in the same country. And even if neighbouring conflict and transborder ethnic kin are empirically associated, we need a group-level assessment to identify whether the new conflict onset actually involves kin groups or other ethnic groups. Especially in the context of tactic diffusion, a strict focus on transborder ethnic kin may be too narrow. As argued in the next sections, shared kin membership can be regarded as part of a more general mechanism of diffusion in which politically similar and geographically proximate ethnic groups can draw inspiration from each other's conflict behavior.

A General Theory of Diffusion: Actors and Channels

There is a considerable sociological literature on central conditions for diffusion, drawing on topics such as protests and social movements. These contributions have not been incorporated in existing research on terrorism, but can extend our understanding of whether and how terrorism diffuses.[10] In brief, it is argued that diffusion requires some degree of similarity and identification points between actors (structural equivalence) as well as linking channels (see e.g. Strang and Meyer, 1993; McAdam and Rucht, 1993; Wejnert, 2002). Among collective actors, structural equivalence may be perceived based on economic factors – such as the level of wealth, the economic system or a similar economic status – and political and cultural factors – such as shared political status, culture, ethnicity, religion, or a common historical background. In the case of collective action the attribution of similarity is not automatic (as in the case of actors with institutionally equivalent roles and functions across countries; cf. McAdam and Rucht (1993); Strang and Meyer (1993); DiMaggio and Powell (1983). For individuals and groups in one country to identify with their counterparts in another, "a non-trivial process of social construction must take place in which adopters fashion an account of themselves as sufficiently similar to that of the transmitters to justify using them as a model for their own actions" (McAdam and Rucht, 1993, p.73). Channels of diffusion linking structurally similar actors can be of two types, namely, relational and non-relational (Strang and Meyer, 1993; McAdam and Rucht, 1993). Channels of transmission can only be relevant for imitation of behavior when actors are aware of structural similarity. Relational diffusion is the spread and adoption of ideas, practices, and strategies as mediated by direct interpersonal or intergroup contacts. This, in turn, is related to a strictly spatial process of diffusion where geographic proximity leads to cross-national diffusion. Non-relational channels are mainly represented by information about a certain phenomenon or practice,

[10]Horowitz's work (2010) is a notable exception in this regard.

available for instance through the media (such as television and the internet), and therefore do not require direct relational ties between actors. In this case, connectedness is determined exclusively by non-spatial factors and diffusion involves geographically distant actors. An additional element which can mediate the communication process between actors is given by social networks and weak ties in general (cf. Wejnert, 2002). These facilitate the flow of information and create elements of identification between actors, whether individual or collective. For example, studies have investigated the spread of innovations among networks of physicians and among businessmen from the same universities (see Wejnert, 2002). Moreover, networks may entail relational as well as non-relational channels of communication. A final element to consider in a theory of diffusion is the existence of gating factors (Wejnert, 2002). These represent characteristics of the environment and actors themselves which affect the likelihood of diffusion indirectly by providing permissive conditions. In other words, these factors create objective feasibilities of adoption of a certain type of behavior or strategy and therefore may have potentiating or inhibiting effects. For instance, in the case of terrorism some contextual factors tend to be negatively associated with the emergence of terrorism in the first place, such as a repressive regime type. This, in turn, may reduce the impact of diffusion factors in that particular country. Conversely, country characteristics that are conducive to terrorism may ultimately amplify diffusion effects.

The Diffusion of Ethnic Terrorism: Exclusion, Proximity, and Emulation

I now apply this theoretical framework to the diffusion of terrorism. I introduce a specific mechanism of diffusion based on the interaction of geographic proximity and structural equivalence between groups in terms of shared political marginalization or exclusion. Groups can adopt terrorism as a tactic to advance their political goals, and can be inspired by different ideologies or "ideas, beliefs, values and principles" through which terrorist "groups define their specific political identity and goals" (Drake, 1998, p.54). Terrorist ideologies can include ethnonationalist/separatist, religious, ethno-religious, leftist (e.g. Communist, Marxist), rightist, racist etc. Historically, the most common type has been ethnonationalist terrorism, that is, terrorism perpetrated by organizations which claim to represent specific ethnic groups, and often linked with separatist claims. In some cases the ethno-nationalist ideology of the group may also have a religious component (ethno-religious groups) as in the case of organizations such as Hamas and al-Qaida in Iraq[11]. Notable examples of ethno-nationalist and ethno-religious terrorism include, among others, the IRA (Irish Republican Army), ETA (Basque Fatherland and Freedom), PKK (Kurdistan Workers Party), LTTE (Liberation Tigers of Tamil Eelam), Hezbollah, Hamas, al-Qaida in Iraq, the Taliban.

Ethnic conflicts have often become a matter of international concern beyond the immediate violence due to the risk that these conflicts may diffuse to neighboring countries and engulf larger regions in fits of ethnic insecurity and violence (Lake and Rothchild, 1998*b*, p.3). For instance, the early 1990s have witnessed a wave of ethnic conflicts that spread across parts of Europe, the former Soviet Union, and Africa thus lending credit to, and even reinforcing, fears that ethnic conflict may be contagious. Similar concerns apply to the specific tactics that groups use, including ethnonationalist or ethno-religious terrorism, which can be adopted both within and outside ongoing civil wars Figure 1 shows the adoption of terrorist tactics by ethnic groups between 1970 and 2009. The blue areas are spatial polygons representing the geographic settlements of ethnic groups which have adopted terrorist tactics based on the Geo-EPR data (Wucherpfennig et al., 2011). The data on terrorist activities of organizations claiming to represent specific ethnic or ethno-religious groups come from a new dataset

[11] Note that this is quite different from purely religious terrorist organizations whith no specific ethnic claims such as al-Qaida in the Islamic Maghreb, Boko Haram, al-Shabaab etc.

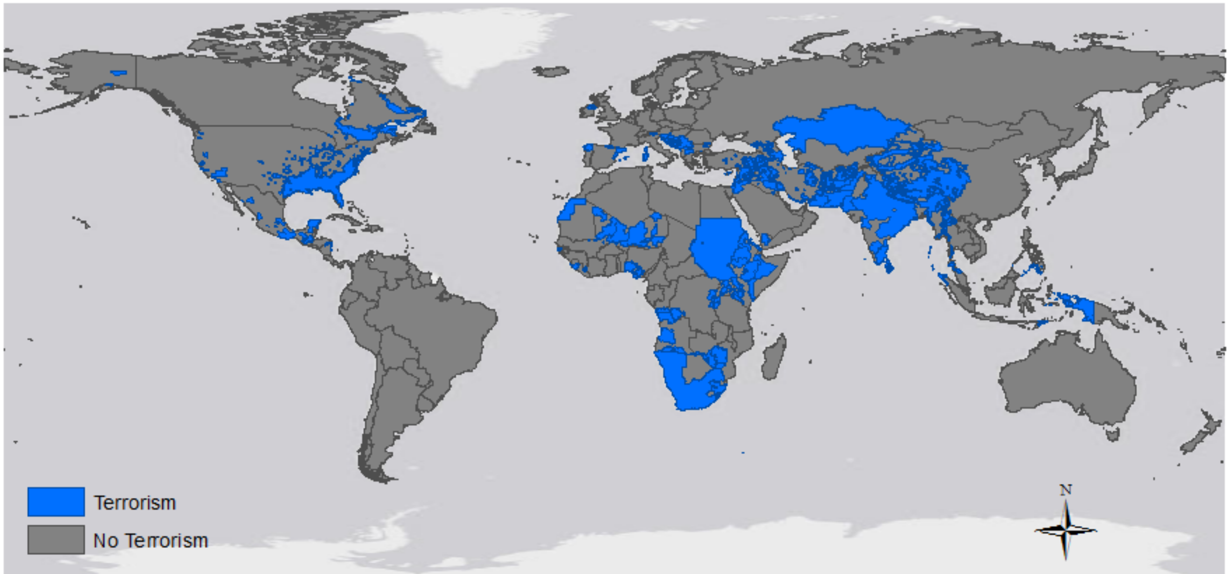

Figure 1: Ethnic Terrorism 1970-2009

described in the data section. It is clear from figure 1 that the adoption of terrorist tactics is not random, but seems concentrated in some geographic areas while absent in others.

Empirical studies of civil war contagion have highlighted the role of geographic proximity to the conflict source. Yet, geography may only tell part of the story about diffusion, and specific ties such as transborder ethnic linkages (e.g. Buhaug and Gleditsch, 2008) and refugee flows (Salehyan and Gleditsch, 2006) also seem important. Some studies suggest that identification between groups with similar characteristics and circumstances is essential for demonstration effects and subsequent conflict diffusion (see e.g. Lake and Rothchild, 1998*a*). Yet, the relationship between spatial proximity and identification remains unclear. On the one hand, strong ties are more likely to emerge between groups living close to each other and with greater opportunities for direct interactions as well as because information flow is easier between proximate groups. Alternatively, geographic proximity itself may be altogether irrelevant and other mechanisms, such as information available through non-relational channels or other forms of weak ties (Granovetter, 1995), lead similar groups in different parts of the world to adopt similar violent strategies to advance their goals (Beiser, 2012). Yet, this by itself does not fully explain why we observe geographic clustering in ethnic terrorism. It could be that information is important but geography amplifies this effect because information flow and direct contacts are likely to be more intense between proximate groups facing similar circumstances. If so, most terrorism diffusion would still occur at a local and regional level. Furthermore, groups sharing similar culture and history are also likely to be geographically close to each other even when not direct neighbors (as in the Arab Spring).

The transnational dimension of grievances and opportunities

Existing studies on the determinants of terrorism focus mainly on the domestic situation of a country or, less commonly, on the relationship between countries. Domestic determinants are generally divided into factors influencing groups' grievances and factors which provide opportunities for the use of terrorism. It is commonly argued that grievances alone do not suffice to cause political and violent mobilization (Fearon and Laitin, 2003), but that "the disaffected begin mobilizing when at least one person from their ranks reaches the conclusion that the time is ripe and devises a strategy for shaping political outcomes" (Hill, Rothchild and Cameron, 1998, p.61). The adoption of terrorism by ethnic groups in other regions or countries can influence the perception of both grievances and opportunities by groups at home which face similar political circumstances. More specifically, ethnonationalist terrorism perpetrated by similar groups can make an ethnic group more aware of its own grievances and more receptive towards the existence of political opportunities for collective action. Kuran (1998, p.36) argues that motives to ethnically dissimilate are determined partly by the activities of ethnic groups in other states. Ethnic strife within one country "sensitizes people elsewhere to their own ethnic particularities, possibly raising their expectations of ethnic conflict at home" (p.36). Changing patterns in one country can create a domino effect through so-called demonstration effect (Kuran, 1998). According to Kuran, "when ethnic discrimination becomes a dominant theme in the political discourse of country A, the citizens of country B gain more exposure to the idea of such discrimination than they would otherwise. Being more sensitized to it, they start blaming their own disappointment on other ethnic groups" (p.50).

Existing models of domestic terrorism tend to consider grievances and opportunities as domestically determined. However, grievances and opportunities can also have a transnational dimension. Groups can use different tactics and strategies to voice their grievances and achieve their political objectives, including terrorism or indirect targeting. The decision of ethnic groups to use terrorist tactics is not just a function of their own domestic situation (closed polity approach), but is likely to be influenced by the behavior of similar groups abroad or even in the same country. The very perception and political relevance of grievances is not an automatic consequence of horizontal political inequalities (Cederman, Gleditsch and Buhaug, 2013) but may be triggered by demonstration effects from other groups or countries, which heighten the domestic saliency of ethnic issues and ethnic discrimination. When grievances are "activated", ethnic identity becomes a rallying factor that creates further incentives for mobilization.

In addition, for identification to take place there needs to be some connection between the groups, such as similarity in ethnic mix, cultural or religious affinity, or some form of direct interaction. These connections define the "reference groups" whose behavior is relevant to a particular group. As a consequence, similarity and identification are more likely to take place at a regional rather than global level. Moreover, unlike peaceful mass protests and demonstrations, terrorism is a more costly and risky strategy which requires specific skills and resources. A neighboring or geographically proximate group that uses terrorist tactics may facilitate training and planning of operations as well establishing alliances between groups (as in the case of India, the Middle East, and Central America). The behavior and choices of other similar groups can shape the perception of opportunities for the adoption and feasibility of a particular tactic, thereby changing cost-benefit calculations.[12]

Structural equivalence is complemented by relational and non-relational channels of communication (Simmons, Dobbin and Garrett, 2008). Direct interactions are not always necessary, but the diffusion of terrorism between ethnic groups is more likely to take place at a regional level. Geographic proximity facilitates the spread of information about other groups' activities and is likely to be associated with similar language, culture and history which facilitate mutual awareness and identification.[13]

The mere flow of information through the media (television, internet etc.) may not be enough to generate identification between ethnic groups and possibly emulation of tactics. In fact not all information is equally relevant for groups, or taken into equal consideration. Individuals and groups select the information that they consider to be relevant for their own decisions and choices, and identification is more likely to occur with groups/actors that are perceived as peers or reference groups for example through shared culture. For instance, a politically excluded Muslim ethnic group in Indonesia is more likely to identify with another Muslim group than, say, with an ethnic group in Guatemala or Congo (where religion is not even a salient issue in conflicts). Indeed, there are a number of Muslim ethnic terrorist organizations fighting for independence in South-East Asia beyond Indonesia, including the Philippines, Thailand, and Myanmar. Finally, the diffusion of terrorist tactics is an inherently asymmetric process whereby external factors operate in combination with conducive

[12] Of course, diffusion can occur between geographically distant actors, but geographic proximity in combination with shared feelings of political marginalization and exclusion facilitates learning about terrorist tactics, mutual identification, and ultimately diffusion.

[13] Proximity can affect the frequency of communication and the intensity of interactions between actors. Therefore it may enhance the spread of information, ideas and strategies and facilitate imitative behavior (Rogers 1983; Wejnert 2002).

conditions at home, thus leading to heterogeneous responsiveness to external stimuli.[14] Some societies are more vulnerable to violence than others and terrorism does not spread everywhere. In particular, ethnic groups are unlikely to be receptive to diffusion processes if they lack the motivation for rebellion in the first place. For instance, dominant or included ethnic groups have few incentives to adopt terrorist tactics even if surrounded by groups that do. Figure 2 summarizes the general mechanism of diffusion of ethnonationalist and ethno-religious terrorism, and reflects the first two testable hypotheses.

H1a: A politically excluded ethnic group i is more likely to adopt terrorist tactics if other similarly excluded groups j in neighbouring regions also use terrorism.

H1b: A politically excluded ethnic group i is more likely to adopt terrorist tactics if other similarly excluded groups in neighbouring countries j also use terrorism.

The two hypotheses differ in the definitions of what constitutes a geographic neighbor (Zhukov and Stewart, 2013). The first hypothesis goes beyond country borders as boundaries of relevant units in diffusion processes, and includes sub-national diffusion where ethnic groups can emulate tactics within the same country as well. The second hypothesis specifically focuses on politically similar groups in neighboring countries, or transnational diffusion. As I expand on in the next section, this is intended to control for the alternative mechanism of competition that may affect groups within the same country, which may compete for the support of the same, or similar, audiences and to obtain concessions from the same government.

[14]For a comprehensive discussion of the role of sender and receiver characteristics in civil conflict contagion, see Metternich, Minhas and Ward (2015)

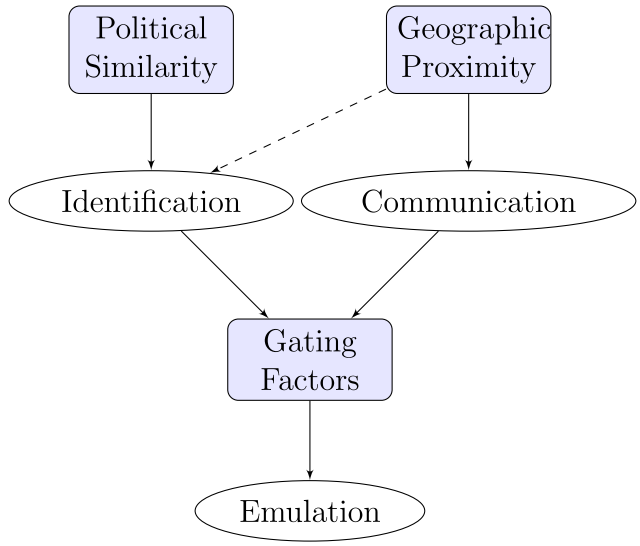

Figure 2: Mechanism of Diffusion

The role of ethnic networks

One particular type of connection between groups, facilitating both mutual identification and the flow of information, is given by transnational ethnic linkages, specifically transborder ethnic kin. The existence of one or more kin group settlements across borders can help establish informal networks between ethnic communities, as illustrated by the case of the Kurds in Turkey, Syria, and Iraq or the Balochs in Iran, Afghanistan, and Pakistan. Existing research on ethnonationalist civil wars has shown the importance of these networks for conflict onset (e.g. Cederman et al., 2013; Buhaug and Gleditsch, 2008), particularly how they can create opportunities for violent mobilization and increase the availability of human and material resources, in addition to providing safe havens for rebel groups in a neighboring country. Here I focus on how the actual behavior of the kin group can affect emulation in a domestic group. This provides an additional explanation for why not all groups with a transborder ethnic kin have mobilized using violence. It also further highlights one specific channel of diffusion of terrorist tactics, based on shared ethnicity and informal networks, which can contribute to unpack the role of geographic proximity. Transnational ethnic linkages operate both as identification factors and well as channels of information about violent tactics, which can travel through these informal ethnic networks. This mechanism leads to two final testable implications:

H2a: An ethnic group i is more likely to adopt terrorist tactics if its ethnic kin in neighboring countries j also uses terrorism.

H2b: An ethnic group i is more likely to adopt terrorist tactics if its ethnic kin in neighboring countries j also uses terrorism and they share a similar political status.

Data and Research Design

To test the hypotheses on the diffusion of terrorism I compile a new dataset of ethnic and ethno-religious terrorism from 1970 to 2009. This links politically relevant ethnic groups in the Ethnic Power Relations Dataset (EPR-ETH, Cederman, Min and Wimmer, 2010) and data on terrorist attacks from the Global Terrorism Database (2013). More specifically, I extract active terrorist organizations from GTD and identify the ethnonationalist and ethno-religious organizations using various sources including the Terrorist Organizations' Profiles (START) and the Armed Conflict to Ethnic Power Relations dataset (ACD2EPR dataset, Wucherpfennig et al., 2012). To link terrorist organizations with corresponding ethnic groups I collected information on whether organizations claim to represent a specific ethnic group, complementing the information in the ACD2EPR with additional research on organizations not involved in a civil war. The dependent variable is a binary indicator based on one or more attacks perpetrated by organizations linked to an ethnic group per year. Only domestic terrorist attacks are considered, and I exclude attacks perpetrated by ethnic organizations in other countries.

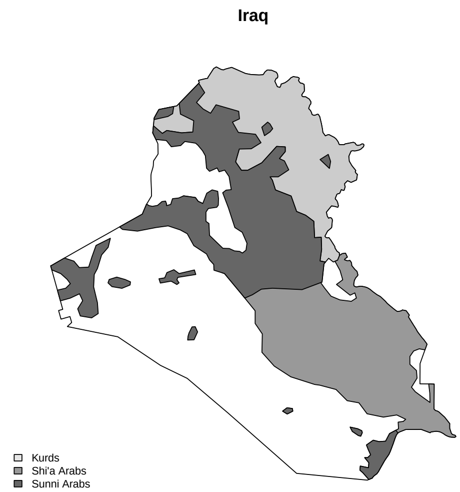

Figure 3: Ethnic group polygons in Iraq

To estimate diffusion I rely on spatial models where a connectivity matrix **W** specifies the dependence structure between the politically relevant ethnic groups in every given year.[15] I have generated two sets of spatial weights matrices that reflect the two different measures of connectivity presented in the theory, namely geographic proximity and political similarity.

I measure geographic proximity between ethnic groups using GeoEPR, a geo-referenced version of the EPR-ETH dataset, which encompasses information on the specific settlement areas (polygons) of ethnic groups from 1946 to 2009. GeoEPR includes 812 group polygons and over 700 unique ethnic groups. In fact many of these group polygons are not fixed but change over time reflecting the emergence of new countries or changing settlements within countries.[16] For each year from 1970 to 2009 I calculate the minimum distance between each group polygon and all other polygons and generated a binary connectivity matrix for each year.[17] Figures 3 and 4 display the settlement patterns and related spatial polygons of

[15]For a general discussion of spatial analysis see Anselin (2003).
[16]Notice that for territorially dispersed groups the settlement polygons coincide with the country polygon.
[17]I have used two different thresholds to define neighbors, as explained in the next paragraphs.

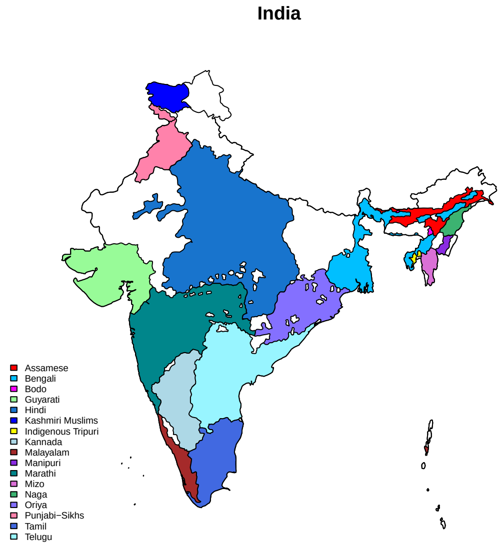

Figure 4: Ethnic group polygons in India

politically relevant ethnic groups in Iraq and India from the GeoEPR.

Political proximity is defined based on whether two groups share the same political status, using the EPR coding as either excluded or included. Based on the political status of each ethnic group for every given year I construct a binary matrix of political similarity where elements are 1 if if two groups have the same political status (both included or both excluded) and zero otherwise.[18] For each year the two matrices are multiplied element by element (i.e. Hadamard product) so that each element (or weight) w_{ijt} of the final matrix represents the product of elements w_{ijt} of the original two matrices. This reflects the combination of political and geographic proximity as posited in the theoretical argument (spatial and non spatial weights). The matrices are then combined into a single $NT \times NT$

[18] The theoretical argument emphasizes the role of political exclusion as a source of structural equivalence. This aspect is explicitly accounted for in the construction of the spatial lags and through the inclusion of variables which capture the degree of political exclusion of each group. However, when constructing the matrix of political similarity it is necessary to code politically similar groups as 1 even if both included because coding included groups as having zero neighbors would automatically generate a singular matrix which makes it impossible to estimate a spatial econometric model such as the spatial probit discussed later

block diagonal matrix which is also row-standardized. Although row-standardization has sometimes been questioned on theoretical grounds (Neumayer and Plümper, 2012), it does not seem particularly problematic on substantive grounds because the theoretical argument does entail that the actual number of neighbors should effect a group's decision to resort to terrorist tactics. Having at least one politically similar proximate group which already adopts terrorist tactics should increase the likelihood of adoption, but the effect need not necessarily increase linearly with the number of neighbors. Row-standardization gives a higher weight to a case where a group has only one neighbor adopting terrorism compared to a case with several neighbors where only one of resorts to terrorist tactics. Furthermore, as detailed in the following sections, the empirical models take into account the conditional responsiveness of groups to spatial stimuli depending on whether they have political grievances or not (i.e. gating factors). In order to measure the effect of trans-border ethnic kin (TEK) I create a dummy variable which takes the value of 1 if a group's kin in a neighboring country uses terrorist tactics and zero otherwise. In fact it was not possible to create an additional weight matrix for these since many ethnic groups do not have a kin neighbor.[19] Data on trans-border ethnic kin are taken from Cederman et al. (2013). The variable is also temporally lagged. To control for domestic motives for terrorism I include dummy variables on the political status of ethnic groups (Cederman, Min and Wimmer, 2010) which reflect the type of political exclusion, with included groups as reference category. I also add the size of the ethnic group to control for domestic resources for mobilization. Data on political status and group size are both taken from the EPR-ETH dataset. Additional control variables include a cubic polynomial of time since last event, real GDP per capita (logged), the level of democracy and a media density index (Warren, 2014). The latter is particularly important since media flows may represent an alternative channel of diffusion.

I estimate two logit models with an observational spatial lag temporally lagged (sometimes

[19]This would in fact generate a singular matrix which by definition cannot be inverted.

called naïve models) and a spatial probit model estimated by Bayesian Markov-Chain Monte Carlo (Wilhelm and Godinho de Matos, 2013; LeSage and Pace, 2009). The main difference between the two models with an observational spatial lag is given by the construction of the **W** matrix. In the first model the spatial lag is calculated considering as neighbors all politically similar ethnic groups within a minimum distance of 200 km. In the second case, only the politically similar groups in first-order neighbor countries are considered, hence I exclude from the neighbors' list all groups within the same country. This to avoid two possible issues; First, there are some instances where multiple ethnic groups are represented by the same organization and this may inflate the effect of diffusion (although there are very few cases of this kind, e.g. Sudan, Nepal, Nicaragua). Second, the observed effects could be due not only to emulation between groups but also to the alternative mechanism of competition. However, if this mechanism is indeed at work, it is only likely to affect ethnic groups fighting against the same government and possibly sharing similar audiences.[20] Thus, excluding groups within the same country may help control for alternative mechanisms of diffusion and set a harder test for the emulation mechanism.[21] In both cases the value of the spatial lag is automatically set to zero for included groups since these groups lack the motives for rebellion in the first place (whether through terrorism, civil war or other violent strategies) and thus are unlikely to be receptive to violent strategies of similar groups elsewhere (domestic motives as gating factors).[22] In both cases the observational spatial lag is also temporally lagged to avoid simultaneity bias.[23] The two models with an observational spatial lag also differ in that for the second model, which only considers ethnic groups in

[20]Ethnic groups represent rather distinct audiences for the respective organizations, especially in the case of secessionist movements.

[21]On the other hand, competition between terrorist organizations is not relevant in this case since the unit of analysis is the ethnic group and not the terrorist organization.

[22]An alternative specification could be to interact the spatial lag with a variable capturing political exclusion.

[23]Any simultaneity bias would be limited to observations where the spatial lag is not set to zero (ethnic groups sensitive to diffusion effects).

neighboring countries, the spatial lag takes the form of a dummy variable which measures whether at least one group in the neighborhood has adopted terrorist tactics in the previous year (rather than their weighted average).

The estimation of a spatial probit model represents a more complex approach as compared to the naïve models. Suppose we have the following spatial autoregressive model (SAR):[24]

$$y^* = \rho \mathbf{W} y^* + \mathbf{X}\beta + \epsilon, \qquad \epsilon \sim N(0, \sigma_\epsilon^2 \mathbf{I}_n) \tag{1}$$

where y^* is the continuous latent outcome variable, $\mathbf{W}$ is an $N \times N$ connectivity matrix which captures the spatial interdependence between units, the parameter ρ is the coefficient for the effects of other units' outcome through this type of connectivity as specified in the $\mathbf{W}$ matrix, $\mathbf{X}$ is an $N \times k$ matrix of covariates, and β is a $k \times 1$ vector of coefficients associated with the k covariates. In this model the latent variable is unobserved. Instead what is observed are the binary outcomes (0, 1) as:

$$y_i = \begin{cases} 1 & \text{if } y_i^* \geq 0 \\ 0 & \text{if } y_i^* < 0 \end{cases} \tag{2}$$

The reduced form of equation (1) is:

$$y^* = (\mathbf{I}_n - \rho \mathbf{W})^{-1} \mathbf{X}\beta + (\mathbf{I}_n - \rho \mathbf{W})^{-1} \epsilon \tag{3}$$

where $(\mathbf{I}_n - \rho \mathbf{W})^{-1}\epsilon$ is the reduced-form error term, and where the errors are no longer independent and identically distributed due to the spatial multiplier $(\mathbf{I}_n - \rho \mathbf{W})^{-1}$. The jointly determined error terms represent a considerable estimation challenge due to the need to

[24]Note that for identification σ_ϵ^2 is set to $\sigma_\epsilon^2 = 1$ for probit.

compute an n-dimensional integral which becomes analytically intractable even for relatively small n (see also Franzese, Hays and Cook, 2016).

The Bayesian MCMC approach is a simulation-based method. The basic idea in Bayesian estimation is to sample from the posterior distribution of the model parameters $p(y^*, \beta, \rho|y)$ given the data and some prior distributions for the parameters. The sampling from the posterior distribution can be realized by a Markov Chain Monte Carlo and Gibbs sampling scheme, where we sample from the following three conditional densities (Wilhelm and Godinho de Matos, 2013, p.131):

$p(y^*|\beta, \rho, y)$, which is the probability of the latent response (continuous) conditional on the observed data and the model parameters (a multivariate normal distribution truncated at zero);

$p(\beta|y^*, \rho, y)$, which is a multivariate normal distribution for the conditional probability of β parameters;

$p(\rho|\beta, y^*, y)$,[25] which is the probability of ρ conditional on the other parameters, the latent response, and the observed response, and where sampling is done using a Metropolis Hastings algorithm.

The Bayesian estimator of the spatial probit introduced by Wilhelm and Godinho de Matos (2013) follows the Bayesian Gibbs sampling approach proposed by LeSage (2013) and LeSage and Pace (2009) with some modifications to facilitate implementation, especially for a relatively large sample size. One of the advantages of this approach is that it overcomes the problems in estimating the standard error in other algorithms (such as the EM algorithm, McMillen (1992)), since measures of uncertainty are derived from the posterior parameter distributions (marginal posteriors). For computational efficiency, the spatial probit is esti-

[25]Note that the posterior distribution of ρ is not a standard distribution, hence sampling from this conditional posterior is done using a Metropolis-Hastings algorithm within the Gibbs sampler.

mated on a subset of the main dataset, that is, two cross-sections of all ethnic groups from 1991 to 1999 and from 2000 to 2009, where values of the dependent variable are averaged over each time period. To avoid post-treatment bias the average values of the group-level covariates are calculated using only the years up to the first observed terrorist attack for each ethnic group. Moreover, in this set-up direct effects and indirect effects (spatial feedbacks) de facto occur simultaneously and therefore the aggregated data reflect the long-run steady state equilibrium. An additional step would be to estimate the models considering values of the dependent and independent variables in each year. The size of data set, which has more than twenty-two thousand observations, makes it very computationally intensive to estimate a Bayesian spatial probit over the full dataset.

Empirical Analysis and Discussion

The empirical results for the two logit models and the Bayesian spatial probit are shown in tables 1, 2 and 3. The results from all models are consistent with the theoretical expectations that an ethnic group is more likely to adopt terrorist tactics if other politically similar and geographically proximate ethnic groups also use similar tactics. More specifically, the coefficient for the lag of terrorism from excluded groups in neighboring region, regardless of country, is positive and highly significant as is the coefficient for the spatial lag of terrorism from excluded groups in neighboring countries. Likewise, the positive effect of terrorist tactics from trans-border kin groups is also supported by the models.

Before evaluating the results from the spatial probit, it is important to assess convergence of the MCMC algorithm. A graphical inspection of all chains through trace plots is a first step, since this often reveals non-stationarity and potentially slow mixing of the chain (p.253 Jackman, 2009). Appendix A reports trace plots for the spatial correlation parameter

Table 1: Logit models with observational spatial lag (w/ media index)

	NB country	NB region	TEK all	TEK similar
Terrorism obs. splag $_{lag}$	2.111***			
	(0.156)			
Terrorism obs. splag $_{lag}$		4.499***		
		(0.656)		
Terrorism TEK $_{lag}$			1.902***	
			(0.200)	
Terrorism TEK similar $_{lag}$				1.976***
				(0.210)
Regional Autonomy	0.440	0.588	1.045**	1.027**
	(0.346)	(0.353)	(0.344)	(0.343)
Powerless	0.817**	0.870**	1.274***	1.260***
	(0.293)	(0.305)	(0.297)	(0.296)
Discriminated	1.095***	1.546***	1.400***	1.383***
	(0.318)	(0.295)	(0.308)	(0.309)
Separatist	1.606**	2.087***	2.282***	2.266***
	(0.490)	(0.418)	(0.415)	(0.415)
Group size	0.253	0.234	0.203	0.190
	(0.413)	(0.387)	(0.396)	(0.397)
Media Density Index	0.005	0.003	0.004	0.004
	(0.003)	(0.002)	(0.002)	(0.002)
Xpolity	0.089***	0.118***	0.109***	0.110***
	(0.024)	(0.023)	(0.025)	(0.025)
GDPpc$_{log}$	−0.268*	−0.069	−0.169	−0.171
	(0.123)	(0.109)	(0.119)	(0.119)
Constant	−0.079	−1.519	−0.804	−0.780
	(0.919)	(0.848)	(0.882)	(0.881)
Wald χ^2	1018.62***	838.86***	1041.89***	1034.02***
Pseudo R^2	0.47	0.45	0.43	0.43
Log-Likelihood	−1763.68	−1796.51	−1895.01	−1891.91
Number of clusters	727	671	727	727
Number of observations	16564	15491	16564	16564

Note: Standard errors in parentheses, clustered by ethnic group.

* p<0.05, ** p<0.01, *** p<0.001 Cubic polynomials not shown in the table.

Table 2: Logit models with observational spatial lag (full sample)

	NB country	NB region	TEK all	TEK similar
Terrorism Obs. splag $_{lag}$	2.034***			
	(0.135)			
Terrorism Obs. splag $_{lag}$		4.721***		
		(0.613)		
Terrorism TEK $_{lag}$			1.657***	
			(0.189)	
Terrorism TEK similar $_{lag}$				1.704***
				(0.196)
Regional Autonomy	0.610*	0.598*	1.076***	1.065***
	(0.281)	(0.287)	(0.264)	(0.263)
Powerless	0.572*	0.529*	0.893***	0.883***
	(0.234)	(0.243)	(0.242)	(0.242)
Discriminated	0.894***	1.244***	1.144***	1.133***
	(0.243)	(0.232)	(0.248)	(0.248)
Separatist	1.049**	1.505***	1.625***	1.615***
	(0.398)	(0.326)	(0.348)	(0.349)
Group size	−0.020	0.025	−0.172	−0.181
	(0.362)	(0.410)	(0.360)	(0.359)
Xpolity	0.070***	0.102***	0.088***	0.088***
	(0.021)	(0.020)	(0.023)	(0.023)
GDPpc $_{log}$	−0.087	0.020	−0.044	−0.044
	(0.073)	(0.072)	(0.077)	(0.077)
Constant	−1.046	−1.668**	−1.162	−1.156
	(0.604)	(0.592)	(0.620)	(0.619)
Wald χ^2	1331.15***	1076.54***	1265.39***	1258.32***
Pseudo R^2	0.48	0.46	0.44	0.44
Log-Likelihood	−2471.43	−2511.98	−2690.69	−2687.89
Number of clusters	766	715	766	766
Number of observations	23500	21864	23500	23500

Note: Standard errors in parentheses, clustered by ethnic group.

* p<0.05, ** p<0.01, *** p<0.001 Cubic polynomials not shown in the table.

and all other model parameters associated with the group-level variables. In addition to visual inspection, I have performed more formal and analytic diagnostics, in particular the Geweke (1992) test of non-stationarity. This convergence diagnostic compares the mean of the MCMC output for every given element of the parameter vector Î¸ across two stages of the MCMC run. More specifically, the Geweke diagnostic takes two non-overlapping parts (usually the first 0.1 and last 0.5 proportions) of the Markov chain and compares the means using a difference of means test to evaluate the null hypothesis that the two parts of the chain are from the same distribution. The test statistics is a standard Z-score with the standard errors adjusted for autocorrelation. Appendix A reports standard Z-scores for all model parameters (model 1 and model 2 in table 3). None of these values is extreme, and in fact the null of stationarity (equality of means between the first 10 per cent and last 50 per cent of the sampled values in each chain) is not rejected for all parameters. The results for the spatial probit in table 3 provide strong support for all the hypotheses. The coefficient for ρ, the spatial autocorrelation parameter, is positive and highly significant which indicates interdependence between the decision of politically similar and geographically proximate ethnic groups to adopt terrorist tactics. The coefficient for trans-border ethnic kin's use of terrorism is also positive and statistically significant.

For the control variables, the different categories of political exclusion, indicating domestic motives yield mixed results. Discrimination and separatist autonomy are positive and highly significant in all the estimated models (both naïve and spatial probit) partly confirming the importance of domestic motives as additional determinants of terrorism. Regional autonomy and powerless groups are more likely to resort to terrorism only in the naïve model, whereas their coefficient is not significant, and often in the opposite direction, in the spatial probit. The size of ethnic groups is not significant in nearly all the models. Democracy is significant only in the naïve models, whereas GDP per capita is negative and significant in the Bayesian model and in one of the naïve models. Moreover, media density appears not to be significant

Table 3: MCMC Spatial Autoregressive Probit (10000 iterations, burn-in = 2000, diffuse priors for β parameters and uniform prior for ρ)

	1991-1999	2000-2009
Discriminated	0.580^{**}	0.514^{*}
	(0.207)	(0.451)
Powerless	-0.108	-0.217
	(0.169)	(0.180)
Separatist	1.256^{***}	1.039^{***}
	(0.366)	(0.376)
Regional Autonomy	-0.044	0.247
	(0.213)	(0.198)
TEK Terrorism	1.031^{***}	1.450^{***}
	(0.201)	(0.212)
Group size	-0.377	-0.566
	(0.331)	(0.380)
Xpolity	0.027	0.003
	(0.019)	(0.018)
GDPpc_{log}	-0.128^{*}	-0.077
	(0.061)	(0.060)
Constant	0.189	-8.077^{*}
	(0.891)	(0.589)
ρ	0.465^{***}	0.503^{***}
	(0.095)	(0.095)
Number of observations	623	630

Note: Coefficients indicate posterior mean. Standard deviation in parentheses
* p<0.05, ** p<0.01, *** p<0.001

for explaining groups' decisions to adopt terrorist tactics. In order to better control for the effect of non-relational channels, particularly those related with the media, I have estimated the spatial probit using a connectivity matrix of political similarity between groups in the absence of geographic proximity. This robustness check are reported in table 4. The spatial correlation coefficient is negative and not significant in this model, thus providing further support for the role of geographic proximity in fostering mutual awareness and identification between politically similar groups. As a consequence, none of these analyses provides empirical support for a global bandwagon among ethnic groups. Rather, the choice of specific violent tactics appears to be determined by regional-level interactions (and the recent adoption of terrorist tactics on the part of Sunni groups fighting in the Syrian civil war, such as Jabhat al-Nusra, appears also consistent with these results).

Table 4: Robustness checks for spatial probit 1991-1999. Political similarity only (excluding geographic proximity from the weights matrix))

	Posterior mean	Standard deviation
Discriminated	0.892^{**}	0.251
Powerless	0.168	0.200
Separatist	1.593^{***}	0.396
Regional Autonomy	0.198	0.239
TEK Terrorism	1.031^{***}	0.229
Group size	-0.272	0.335
Xpolity	0.031	0.023
GDPpc $_{log}$	-0.182^{*}	0.079
Constant	-0.232	0.759
ρ	-0.300	0.447
Number of observations	630	

* p<0.05, ** p<0.01, *** p<0.001

Figure 5 shows the substantive effect of terrorism from excluded groups in a neighboring country in the previous year on the probability that a discriminated group will adopt terrorist

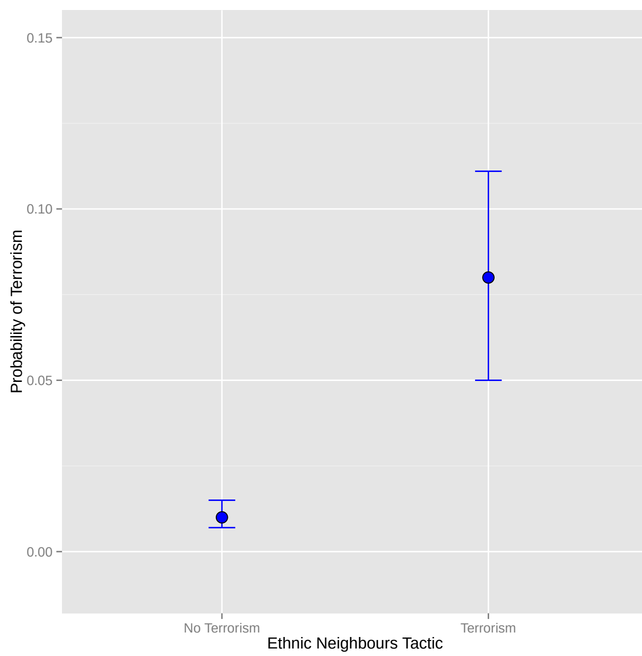

Figure 5: Predicted probability of terrorism for discriminated groups

tactics in the current year, based on estimates from model 1, table 2. The results are shown for discriminated groups, which face the highest level of political exclusion and therefore are likely to have very strong domestic motives for violence even in the absence of terrorism from other groups. Figure 5 indicates that the presence of at least one politically excluded ethnic group which uses terrorism to advance its political goals increases the likelihood of terrorism by a factor of 8.

Marginal effects for the Bayesian spatial probit require a more complex calculation (see Appendix B).[26] Following LeSage et al. (2011) scalar summary measures of direct, indirect, and total effects are presented in tables 5 and 6, for statistically significant variables, based on estimates in table 3. These marginal effects reflect changes in the probability of terrorism relative to a one unit change in the independent variables. In the spatial probit, a change in political exclusion in ethnic group i will not only increase the probability that this groups

[26]For a discussion on the importance of presenting substantive effects for spatial models of diffusion see Franzese, Hays and Cook (2016)

adopts terrorist tactics but will also affect the probability that connected neighboring groups j also resort to terrorism. The magnitude of this effect would depend on proximity between i and j (as defined in the $\mathbf{W}$ matrix) and on the strength of spatial dependence (as measured by the ρ parameter). Political exclusion of group i will then have a direct impact on the probability that group i adopts terrorist tactics as well as an indirect or spatial spillover impact through the effect on neighboring groups j. The total effects here are nearly twice as large as the direct effects, which means that almost half the average total effect from increasing the value of an explanatory variable on the probability of terrorism is due to spatial feedbacks to and from neighboring units (i.e. in the presence of interdependence, the probability that $y_i = 1$ depends not only on x_i but also on all x_j through their effect on y_j). The direct effect of domestic motives on terrorism is certainly important but so are indirect effects. Two types of exclusion, namely, regional autonomy and powerless without discrimination do not seem to have a significant direct effect on terrorism. However, groups in similar situations are still exposed and sensitive to spatial spillovers from other groups.

Figures 6 and 8 show disaggregated spatial effects from the spatial probit for two ethnic groups, namely the Kurds in Turkey and Sunni in Iraq, and their respective neighborhoods.[27] More specifically, these figures show how political exclusion of these groups not only has an effect on the likelihood that these groups adopt terrorism but, through this effect, it also influences other groups' adoption of terrorist tactics. In the case of Kurds in Turkey I have used the actual status of the group between 1990 and 1999, namely, discriminated to generate these probabilities. In the case of the Sunni in Iraq I consider a scenario where this group is actively discriminated.[28] The maps illustrate how a change in the political status of both groups towards discrimination affects the probability of terrorism not only for these groups but also for all other connected ethnic groups, and different colors in the

[27] These disaggregated effects are calculated using the mathematical formulas reported in Appendix B.

[28] The actual status of the Sunni after 2003 is powerless while they were politically included during Saddam Hussein's regime

Table 5: Average direct, indirect, and total effects from spatial probit 1991-1999 (95% credible intervals)

	Direct Effects		
Variable	Posterior Mean	Lower Bound	Upper Bound
Discriminated	0.099	0.039	0.164
Separatist	0.214	0.106	0.338
TEK Terrorism	0.176	0.108	0.249
GDP pc	-0.022	-0.040	-0.005

	Indirect Effects		
Variable	Posterior Mean	Lower Bound	Upper Bound
Discriminated	0.080	0.030	0.138
Separatist	0.171	0.076	0.294
TEK Terrorism	0.142	0.070	0.230
GDP pc	-0.017	-0.034	-0.004

	Total Effects		
Variable	Posterior Mean	Lower Bound	Upper Bound
Discriminated	0.177	0.075	0.285
Separatist	0.385	0.201	0.593
TEK Terrorism	0.318	0.203	0.448
GDP pc	-0.039	-0.072	-0.009

Table 6: Average direct, indirect, and total effects from spatial probit 2000-2009 (95% credible intervals)

	Direct Effects		
Variable	Posterior Mean	Lower Bound	Upper Bound
Discriminated	0.076	0.021	0.138
Separatist	0.153	0.058	0.262
TEK Terrorism	0.214	0.014	0.299

	Indirect Effects		
Variable	Posterior Mean	Lower Bound	Upper Bound
Discriminated	0.070	0.020	0.130
Separatist	0.142	0.051	0.254
TEK Terrorism	0.200	0.110	0.311

	Total Effects		
Variable	Posterior Mean	Lower Bound	Upper Bound
Discriminated	0.145	0.045	0.253
Separatist	0.295	0.118	0.490
TEK Terrorism	0.413	0.283	0.565

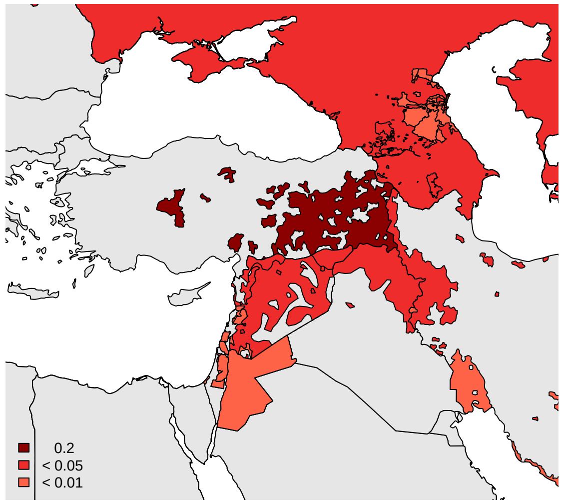

Figure 6: Spatial effects of the probability of terrorism for Kurds in Turkey and connected ethnic groups following a shock to the political status of Turkish Kurds towards discrimination (model predictions 1991-1999)

map are associated with different probabilities of domestic terrorism, based on the model estimates.[29] Moreover, while figure 6 presents the predicted probability of terrorism for the Kurds and their neighborhood based on the model, figure 7 reports the ethnic groups who actually adopted terrorist tactics in the same region during the time period considered. This comparison shows how several of the ethnic groups associated with an increased probability of terrorism based on the model have in fact adopted terrorist tactics.

I also examine the probability of terrorism for an ethnic group conditional on the actual adoption of terrorist tactics by a similar, connected, group in the region using the parametric simulation approach introduced by Franzese, Hays and Cook (2016). I focus specifically on Sunni groups in Iraq and Syria, and find that the actual use of terrorism by Sunni

[29]The calculation of these spatial effects is also very intensive because, unlike non-spatial model, these effects take the form of a matrix for each of the model parameters. In order to obtain confidence intervals the 10000 sampled values need to be used (or at least a random sample of them) and the $(\mathbf{I}_n - \rho\mathbf{W})^{-1}$ matrix has to be inverted at each iteration. In the appendix I provide the mathematical formulas used to calculate these for specific neighborhoods.

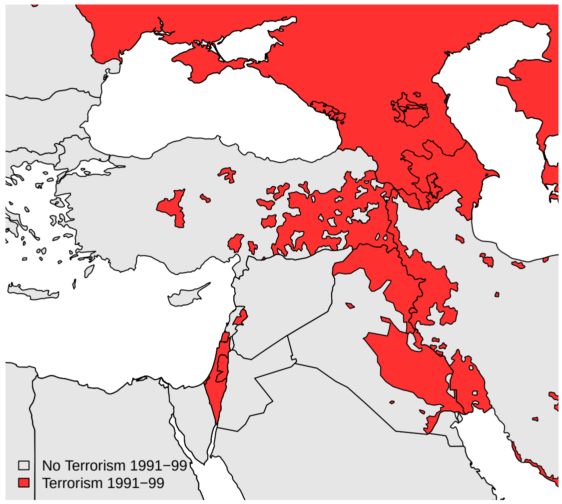

Figure 7: Ethnic groups who actually adopted terrorist tactics between 1991 and 1999 in the same region (for comparison with the above model predictions)

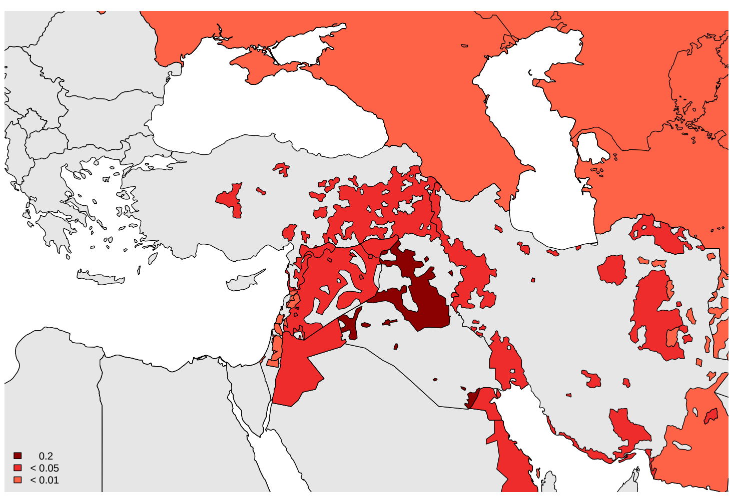

Figure 8: : Spatial effects of the probability of terrorism for Sunni in Iraq and connected ethnic groups following a shock to the political status of Sunni towards discrimination (model predictions 2000-2009)

organizations in Iraq increases the probability of terrorism for Sunni in Syria by 28 per cent.[30]

A binary operationalization of terrorism from politically similar neighboring groups may be criticized because it does not necessarily take into account the magnitude and visibility of terrorist activity or its short-term effectiveness. Isolated terrorist attacks may appear less relevant and therefore less likely to generate emulation from other groups. Table 7 reports results using an alternative construction of the spatial lag which uses a threshold of at least ten terrorist attacks carried out by each connected group in the previous year, and treats lower terrorist activity in the neighborhood as no activity at all (hence coded zero). The results are essentially the same. In this regard, the correlation between the two spatial lags is 0.67, which shows that most of the terrorist activity reported in the data is part of larger campaigns rather than isolated attacks. Recent research also suggests that governments engage in preemptive repression when fearing conflict contagion from neighboring countries (Danneman and Ritter, 2013). Such repression may provide an additional domestic motivation for terrorism besides group-level discrimination. Therefore I have estimated the models controlling for civil war in neighboring countries and results remain consistent.[31]

[30] A detailed description of this procedure in included in Appendix B.

[31] Results included in the supplemental Appendix.

Table 7: Robustness checks for logit model, controlling for magnitude/visibility of terrorism (10 attacks threshold)

	w/media density	w/o media density
Terrorism obs. splag 10 attacks $_{lag}$	5.249***	5.134***
	(0.874)	(0.936)
Regional Autonomy	0.818*	0.831**
	(0.355)	(0.278)
Powerless	1.128***	0.819***
	(0.298)	(0.242)
Discriminated	1.684***	1.390***
	(0.287)	(0.230)
Separatist	2.202***	1.601***
	(0.403)	(0.318)
Group size	0.249	−0.027
	(0.387)	(0.420)
Media Density Index	0.004	
	(0.002)	
Xpolity	0.109***	0.088***
	(0.023)	(0.022)
$GDPpc_{log}$	−0.105	−0.012
	(0.115)	(0.072)
Constant	−1.130	−1.253*
	(0.891)	(0.589)
Wald χ^2	1004.55***	1226.06***
Pseudo R^2	0.43	0.45
Log-Likelihood	−1839.04	−2586.74
Number of clusters	671	715
Number of observations	15491	21864

Note: Standard errors in parentheses, clustered by ethnic group.

* p<0.05, ** p<0.01, *** p<0.001 Cubic polynomials not shown in the table.

Conclusion

This article shows the importance of considering interdependence between terrorist organizations and strategic emulation as a crucial mechanism for the adoption of terrorist tactics. Despite a burgeoning literature on the causes of terrorism, the vast majority of existing studies regards terrorist organizations as independent of each other and the adoption of violent tactics as a purely "domestic" decision, rooted in country-level or, more rarely, group-level characteristics. In fact, even common accounts of domestic terrorism based on grievances and/or opportunities for violent mobilization mainly assume these to be domestically determined. This study focuses instead on the transnational dimension of both grievances and opportunities, and how external events can make ethnic grievances politically salient and shape perceptions of feasibility and effectiveness of terrorist tactics. Rather than simply testing for interdependence of terrorist activities, I introduce a specific mechanism of diffusion, based on the interaction between structural equivalence, in the form of political exclusion, and geographic proximity. Such factors create conditions for mutual identification and awareness, as well as information and communication between groups. This mechanism highlights the importance of peer-group effects as the basis for strategic emulation. These depend not only on structural equivalence, in terms of shared political marginalization, but also on specific connections such as ethnic ties, religious or cultural affinity as well intergroup communication, which are more likely to occur at a regional rather than global level. These elements together contribute to define the so-called reference groups, whose behavior can constitute an "example" for others. All models provide strong support for the theoretical argument and the specified mechanism of diffusion of ethnonationalist and ethno-religious terrorism. To the best of my knowledge this study has been the first to argue theoretically and test empirically, in a global group-level analysis, that domestic terrorism is not a purely domestic phenomenon, rooted in the individual characteristics of groups or countries, but has important external determinants and consequences due to interdependence between groups.

Without taking into account interdependence and strategic emulation it is difficult to understand recent events of domestic terrorism such as the ones occurred in France between 2014 and 2015, and culminated with the attacks against the satirical newspaper Charlie Hebdo which killed 12 people and injured 11. Technically these were domestic attacks, as the venue, perpetrators, and targets all belonged to the same country. Yet, most experts and commentators recognize that their roots are to be found elsewhere; for instance in the connection between domestic grievances and external sources of radicalization whereby disenfranchised young Muslims in France have become more vulnerable to radicalization and violent appeals from Islamist terrorist organizations fighting in other areas of the world, such as the Islamic State (IS) or al-Qaida. Additionally, the Syrian conflict, where terrorist tactics are increasingly widespread, appears to have heightened the risk of domestic terrorism even in Western European countries through the phenomenon of so-called foreign fighters. But the use of terrorist tactics in the Syrian conflict was not independent of the high levels of terrorism around Syria, from ethnic and ethno-religious groups in Iraq, Lebanon, and Turkey.

The new dataset of ethnic and ethno-religious terrorism introduced in this study has allowed to identify the specific ethnic communities from which terrorist organizations could emerge and to provide a global group-level assessment of the role of political marginalization and exclusion in generating political grievances making some groups more receptive towards demonstration effects. At this point it is difficult to study explicitly religious and Islamist terrorism because of the lack of cross-national data on the religious affiliations of ethnic groups and religious terrorist organizations. Yet, future data will permit to extend this frame to this crucial testing-ground for theories of diffusion, where the geographic constraints may be less severe, and non-relational channels such as the Internet and marginalized immigrant communities and diaspora groups may play a more central role.

Future studies could also better integrate the role of the government, particularly state repression. Existing data on repression is primarily available at the country-level and does not allow identifying whether the government represses particular ethnic groups within the population at large. This makes it currently difficult to test hypotheses at the group level because differences in group behavior are not matched by variation in government actions. Finally, advances in spatial econometric methods open several promising avenues for future research, including investigating the diffusion mechanisms of other types of terrorism, such as religious and leftist terrorism, better incorporating media effects in the diffusion of political mobilization whether violent or non-violent, and analyzing the diffusion of non-violent tactics.

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