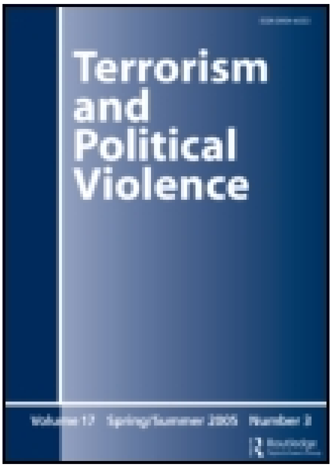

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The Battle for Baghdad: Testing Hypotheses About Insurgency From Risk Heterogeneity, Repeat Victimization, and Denial Policing Approaches

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The Battle for Baghdad: Testing Hypotheses About Insurgency From Risk Heterogeneity, Repeat Victimization, and Denial Policing Approaches

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The Iraqi Insurgency (2003–2011) has commonly been characterized as demonstrating the tendency for violence to cluster and diffuse at the local level. Recent research has demonstrated that insurgent attacks in Iraq cluster in time and space in a manner similar to that observed for the spread of a disease. The current study employs a variety of approaches common to the scientific study of criminal activities to advance our understanding of the correlates of observed patterns of the incidence and contagion of insurgent attacks. We hypothesize that the precise patterns will vary from one place to another, but that more attacks will occur in areas that are heavily populated, where coalition forces are active, and along road networks. To test these hypotheses, we use a fishnet to build a geographical model of Baghdad that disaggregates the city into more than 3000 grid cell locations. A number of logistic regression models with spatial and temporal lags are employed to explore patterns of local escalation and diffusion. These models demonstrate the validity of arguments under each of three models but suggest, overall, that risk heterogeneity arguments provide the most compelling and consistent account of the location of insurgency. In particular, the results demonstrate that violence is most likely at locations with greater population levels, higher density of roads, and military garrisons.

Keywords Baghdad, COIN, insurgency, repeat victimization, risk heterogeneity

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Does variation in the local characteristics of places or counterinsurgency (COIN) activities have the greater bearing upon the location, escalation, and diffusion of insurgent violence[1] at the local level? This article explores the evolution of violent behaviours in the Iraqi capital, Baghdad, at the peak of the Iraqi Insurgency in 2005. Descriptions of the Iraqi Insurgency parallel those of violence elsewhere. Specific locations—including, in this case, Mosul, Kirkuk, Basrah, and areas of Baghdad (e.g., Sadr City)—were highlighted as violent hot spots. Violence escalated and diffused within and between local communities. Insurgent and counter-insurgent forces fought pitched battles at close quarters over the prospect of relatively small territorial gains. In other words, the Iraqi Insurgency—and the Battle for Baghdad, in particular—provides an excellent opportunity to assess competing hypotheses regarding the location and diffusion of violence. To do so, we draw upon influential approaches from Environmental Criminology, which, we argue, are surprisingly under-utilized in the study of insurgency yet provide remarkably powerful accounts of local-level patterns of these violent phenomena. Specifically, we explore expectations derived from logics regarding risk heterogeneity, near repeat victimization (or the contagion of risk), and police disruption and deterrence.

The Battle for Baghdad was a consistent feature of the near nine-year conflict between and amongst Iraqi insurgents and U.S.-led Coalition forces. In its first three years, the insurgency was formed primarily out of anti-Coalition violence and Coalition responses. The violence was re-oriented dramatically after the bombing of the Shia al-Askari mosque in Samarra in February 2006. This bombing resulted in the eruption of ethnic conflict as the primary source of violence, which prompted the U.S. troop surge in the Spring of 2007.[2] This paper focuses on identifying which combinations of local characteristics, COIN activities, and near repeat victimization led to the observed location and diffusion of violence, and accordingly examines the early phase of the conflict. While we focus upon the single case of Baghdad in this article, it is likely that our contribution could speak to insurgent campaigns elsewhere, too.

Burgeoning literatures across multiple disciplines explore the spatial clustering and diffusion of violent political conflict and criminal activities. Different scholars, building various theories and employing diverse methods, typically study these two event types separately. However, in some cases while the theories have different names, and may apply to various spatial scales, similar concepts are explored. For example, in studying terrorist attacks at the country level over time, Manus Midlarksy suggests four mechanisms that might explain why attacks occur where they do, as follows: (a) patterns are simply random; (b) there is heterogeneity such that some countries are more at risk than others, but that the variation in risk across counties is stable over time; (c) a process of reinforcement leads to the risk of attack *within* a country being elevated following an attack in that country; and, (d) a process of *contagion*, whereby attacks in one country temporarily elevate the risk of attacks in those nearby.[3]

Similar mechanisms have been explored in the Environmental Criminology literature to explain patterns of urban crime at the micro level. For example, it appears that the risk of residential burglary is not random, with some neighborhoods, street segments, and households at greater risk than others. Of particular relevance is the finding that the risk of repeat victimization of the same household is highest in the period that immediately follows a burglary.[4] Moreover, following a burglary at one home the risk to those nearby is also temporarily elevated (referred to as near repeat victimization).[5] Possible explanations for such patterns mirror those discussed above. That is, such patterns could simply reflect a simple (random) Poisson process, or be explained in terms of risk heterogeneity (a mixed Poisson process) whereby some homes or neighborhoods are more at risk than others—with this variation in risk being stable over time. In the case of the latter, this would suggest some targets are simply more vulnerable than others, and different offenders target them. An alternative is that the risk of burglary has a contagion-like quality, with the risk of burglary being temporarily elevated following each event. In the event that this is the case, the most parsimonious explanation would be that having successfully targeted one home, the *same* offender subsequently returns to that or nearby (similar) targets.[6] A further possibility is that patterns of crime are explained by a combination of such processes.

We look to build upon the overlap between these two literatures. Both criminal and insurgent activities share some underlying characteristics. First, both sets of actors (insurgents and criminals) are subject to constraints. This is true both in terms of their mobility and the opportunities of which they will be aware and capable of exploiting. Second, both types of activity are the outcome of strategic interactions between multiple actors—criminal and police force, insurgent and military. In other words, the actions of one actor affect the other. The whereabouts of the police or the military directly influences where criminals and insurgents are willing and able to target. In the case that the activity of military or the police suppresses that of their adversary (criminal or insurgent), the latter will aim to avoid the locations the other is deployed to. However, we also recognize that there is an important departure between criminal and insurgent activities with respect to their strategic interaction with the authorities. In particular, insurgency is distinct insofar as it often also involves the direct targeting of the military. By contrast, criminals are most typically motivated to avoid locations being policed.

We offer a multivariate analysis of the local dynamics of violence in the Iraqi capital, Baghdad, across a six-month period in 2005. This analysis is more fine-grained than is typical of analyses of conflict contagion, and is in line with a growing trend towards focusing upon intra-state or internal diffusion. This focus allows for an opportunity to approximate the effect of loci-specific characteristics (risk heterogeneity) on patterns of violence. We also draw upon environmental criminological approaches to the study of repeat victimization to offer a more theoretical account of spatial dependence/escalation between violent events. Finally, we also assess the influence of government actions (policing/COIN activities) upon the clustering and diffusion of insurgent violence.

This article proceeds as follows. First, we highlight key contributions in the extant literature, and highlight competing hypotheses in response to the core research question of the study: Do heterogeneous local characteristics or counterinsurgency (COIN) activities have the greater bearing upon the location, escalation, and diffusion of insurgent and terrorist violence at the local level? These competing hypotheses are derived from logics of near repeat victimization, risk heterogeneity, and the effects of policing. Second, to test these competing hypotheses we design a suitable multivariate research strategy, employing logistic regression models with spatial and temporal lags. Third, we discuss the results of these analyses with a view towards offering academic and policy implications.

Background and Competing Hypotheses

In this section we detail an emerging literature within the conflict processes community that has re-oriented focus towards the sub-national diffusion of conflict and violence. This research pays attention to the tendency for violence to escalate and diffuse at the subnational level—i.e., to trigger more violence at the same and nearby locations, respectively.[7] In doing so, we lay out a series of claims regarding the extant empirical literature on insurgency and terrorism that prompt us to draw upon environmental criminological approaches.

We begin with the broad claim that criminological approaches operate best at the local level, a scale that is typically not the focus of social science studies of insurgency and terrorism, but that is crucial to accounting for local diffusion of events. To this we add three more specific claims. First, we contend that both Political Science and Environmental Criminology enjoy rich traditions of paying attention to the issue of spatial heterogeneity in the distribution of violent and criminal activities. We build upon these traditions via a broad discussion of the importance of paying attention to risk heterogeneity in the local-level study of insurgency. Second, we claim that concepts from research on (near) repeat victimization neatly complement more abstract notions of risk (spatial) heterogeneity and provide a valuable micro-level account of the observation of spatial dependence between insurgent events. Third, we claim that criminological theory regarding the effect of police activity that aims to deter or disrupt criminal activity (hereafter, denial-based policing) can usefully inform expectations regarding the strategic interaction between insurgent violence and COIN activities. Each of these three approaches is used to derive testable hypotheses regarding the local diffusion of insurgent violence.

Research on Risk Heterogeneity

As discussed above, with respect to patterns of (near) repeat criminal victimization, the risk heterogeneity (or flag) hypothesis[8] suggests that space-time patterns of victimization can actually be explained by time-stable variation in risk across potential targets.[9] The idea is that some places will be more vulnerable than others and that this vulnerability will be perceived by a variety of offenders who will exploit it. In the case of burglary, ethnographic research indicates that offenders express common preferences for the characteristics of homes that make them attractive targets.[10] And, research that has explicitly examined this explanation[11] suggests that risk heterogeneity explains some (but not all) of the variation in space-time patterns of burglary, making it an important mechanism to study.

Following the pre-theoretical framework of Benjamin Most and Harvey Starr, we suggest, in turn, that risk heterogeneity is reflected in the distribution of local factors that affect insurgents' opportunities and willingness to carry out violent attacks.[12] Two potential sources of the spatial pattern of insurgency are highlighted in the existing literature: local infrastructure and communication networks, as well as demographic distributions. In both cases, it is argued that the distribution of violence simply reflects the similar distribution of one or more of these local attributes; the likelihood of violence across a set of locations is assumed to vary according to the characteristics of those locations. Moreover, the local presence of infrastructure and specific demographic distributions alters both the opportunity for and the willingness of insurgents to carry out an attack.

A key characteristic of the Iraqi Insurgency was the employment of improvised explosive devices (IEDs). Indeed, it is estimated that IEDs accounted for 63% of Coalition casualties through to the end of 2007.[13] Given that these were most typically deployed in the form of roadside bombs targeting military patrols, it seems reasonable to contend that the presence of and access to road networks played a pivotal role in determining the location of insurgent activities in Iraq. This relationship has been demonstrated in the case of recent violence in the North Caucasus. In his study of the region, Yuri Zhukov offers a comprehensive theoretical and empirical treatment of the role of road networks in insurgent campaigns. He demonstrates that road networks are the most important factor in determining where conflict is located and to where it is able and likely to spread.[14]

A second element of infrastructure that is speculatively associated with increases in the opportunity for insurgent activity is cellular (mobile) phone technology. This technology is thought by some to have been an "explosive technology for insurgents" in Iraq.[15] Jacob Shapiro and Nils Weidman comprehensively demonstrate, however, that areas enjoying increased cell phone technology coverage actually observed reductions in insurgent violence between 2005 and 2008. They posit that this is likely because local cell phone coverage enhances counterterrorism opportunities and capabilities more readily than it aids insurgents.[16]

With respect to risk heterogeneity, therefore, we have an initial expectation that the likelihood of attacks at a specific location is conditioned by opportunities afforded by the availability of infrastructure:

> *Hypothesis 1* (*H1*): Higher levels of insurgent activity are expected at locations at which local infrastructure provides an opportunity for insurgents to carry out attacks.

To better understand the impact that risk heterogeneity has upon the willingness to carry out attacks, we look to the distribution of populations. To assess the effect of the 2007 surge upon Iraqi quality of life, John Agnew and colleagues draw upon data from nighttime light satellite imagery. This data (from the Defense Meteorological Satellite Program-Operational Linescan System [DMSP-OLS]), at 2.8 km pixel resolution is viewed as denoting that the local population has access to electricity. They demonstrate that other populated areas observed increases in nighttime light activity but Baghdad experienced a decrease. Hence, the observed decrease in violence most likely should not be attributed to COIN activity but, rather, to the fact that large portions of the city's population were displaced.[17]

It has also been demonstrated that demographic distributions matter insofar as they reflect the divisions that emerge between ethnic groups. Using a computational model, Nils Weidmann and Idean Salehyan explore violence in Baghdad in the context of inter-ethnic relations. They pay attention to the underlying distribution (or segregation) of distinct ethnic groups and the effect of likely migration patterns upon subsequent patterns of violence. In addition, their agent-based model (ABM) is used to quantify the likely impact of hypothetical changes in the local provision of policing. The model suggests both that violence is driven by patterns in ethnic populations rather than prior violence, per se, and that even small changes in policing (notably early interventions in response to violence) could pay significant dividends. They conclude that the troop surge of 2007 mitigated levels of violence.[18]

In the Weidman and Salehyan ABM, agents respond to their co-ethnics by choosing whether to engage in violence or instead move to a safer neighborhood. This aligns with the broader literature on Iraq, which suggests that frequent interactions between rival ethnic groups best account for the violence that continues to plague Iraq to this day. This literature has tended to conclude that any post-surge peace dividend resulted not from increased COIN activity but, rather, from separation resulting from inter-ethnic cleansing.[19] Elsewhere it is suggested that the violent conflict that erupted between Shia and Sunni militias came about not just because of the ethnic cleavage within Iraqi society but also because of the maintenance of the U.S. occupation.[20]

Whether driven directly by ethnic cleavages or, rather, simply the presence of suitable targets, we anticipate that the likelihood of attacks at a specific location is conditioned by the willingness to target populations:

> *H2:* Higher levels of insurgent activity are expected at locations with high populations, because they define greater willingness for insurgents to carry out attacks.

Research on (Near) Repeat Victimization

It is well established that individual episodes of violence within broader sub-national conflicts commonly exhibit spatial dependencies.[21] However, papers revealing such patterns rarely offer detailed accounts of the factors driving them. Whilst both Environmental Criminology and Political Science share in common the employment of the disease analogy to describe the distribution and potential diffusion of criminal and violent political activities, respectively, the former has the stronger tradition of offering micro-level accounts of these distributions.

Early research concerned with the spatial analysis of crime examined patterns at spatial scales such as provinces[22] or zones within cities.[23] But in the last three decades, the focus of both empirical and theoretical research has been directed towards patterns at the micro level of places, where places might refer to street segments,[24] individual locations such as homes,[25] or particular facilities.[26] The motivating principle of so doing is that crime events occur when there is a convergence in space and time of offenders, suitable opportunities for crime, and the absence of capable guardians, whoever or whatever they might be.[27] These convergence settings occur at specific micro level places and hence there is an increasing interest in studying patterns of crime at the micro, rather than meso or macro levels.

Demonstrating the utility of this approach, research shows that particular types of places are more at risk than are others and that there exist sharp discontinuities in risk, such that while one home or one street segment might be at a high risk of victimization, those adjacent or nearby need not be.[28] In addition to examining variation in risk across places, research increasingly examines how risk varies over time at the micro level of place. As discussed, research on burglary victimization (for example) indicates that once victimized a home is at an elevated risk in the future, but this elevation in risk decays at an exponential rate. While theories of risk heterogeneity could explain such patterns, the difference in risk across homes necessary to do so would be unrealistic and computer simulation experiments demonstrate that risk heterogeneity alone is unlikely to explain observed patterns.[29] The alternative explanation is that one offence temporarily influences the risk of victimization at the burgled home, most likely because repeat victimization is the work of a returning offender. According to this perspective, having victimized a home, the offender acquires new knowledge about that location such as the likely risks and rewards associated with returning to commit further offenses. However, as this knowledge will be forgotten[30] or the perceived accuracy of it will fade over time, according to this perspective a swift return to previously victimized homes is anticipated to be likely. Interviews with offenders[31] and the analysis of crimes detected by the police[32] support this view.

If offender learning associated with their victimization of particular places does shape the likelihood with which offenders will return, logic—encapsulated in the offender as forager hypothesis[33]—suggests that it will also temporarily affect the likelihood of them targeting those nearby (referred to as *near* repeat victimization to differentiate it from repeat victimization of the exact same location). To explain, the first law of geography states that things that are close to each other are more similar than those further apart[34] and hence acquired knowledge (e.g., ease of access, levels of natural surveillance, likely rewards) that is relevant to one location is likely to apply to those nearby. As with repeat victimization of the same home, uncertainty as to the accuracy of this knowledge will increase with elapsed time. And, while such learning could increase the risk of burglary at particular locations permanently, returning to the same locations repeatedly will eventually incur an elevated (perceived or actual) risk of apprehension for the offender, and hence the offender as forager is expected to move on. Work on "near repeat" victimization has used techniques originally developed to detect disease contagion—such as a variant of the Knox Test—to see whether the elevated risk associated with repeat victimization of the same home does extend to their neighbors.[35] A great many papers so far published suggest this to be the case, and while the precise patterns vary across locations and crime types, a typical characterization is that the risk of (say) burglary is elevated for homes within 200 m of the burgled home for about two weeks.[36] Moreover, interviews with offenders,[37] the analysis of crimes detected by the police,[38] and computer simulations[39] suggest that the reasons for these patterns are consistent with the offender as forager hypothesis.

Statistical techniques initially developed to detect disease contagion[40] have been used to show that in the case of residential burglary[41] and other crimes,[42] events cluster in space *and* time, and do so more than would be expected if the risk of crime could be explained in terms of risk heterogeneity alone. Other work uses micro-simulation[43] and agent-based models[44] to examine the extent to which the two types of processes—risk heterogeneity and contagion—have a part to play in generating space-time patterns of burglary, and suggests that *both* explanations are required to explain the precise patterns.

Inspired by the work concerned with urban crime, more recent work has employed the statistical approach described above to examine patterns of Improvised Explosive Device (IED) attacks in Iraq and similar violence elsewhere.[45] In one instance, criminological research has been employed to motivate analysis of so-called "microcycles" of violence as a means of identifying evidence of burstiness in events. Work in this vein has attempted to move beyond mere characterization of global space-time dependence to be able to account for the role of individual events in the genesis of localized bursts of activity—the microcycles. Evidence of microcycles has been uncovered in the cases of Euskadi Ta Askatasuna (ETA) violence in Spain and Frente Farabundo Martí para la Liberación Nacional (FMLN) violence in El Salvador.[46]

Along similar lines, Shane Johnson and Alex Braithwaite have articulated a series of expectations as to why such patterns might be anticipated. Attrition-based strategies encourage insurgents to concentrate their efforts on specific local targets to exhaust their opponents' willingness to continue to engage. At the same time, insurgents use the evidence of these concentrations of attacks as a means of building morale amongst their support bases. The repeated targeting of a location acts, in other words, as a demonstration of the insurgents' collective ability to impose its will against the government and occupying forces.[47] These arguments regarding the propensity for insurgents to cluster their attacks in space and time are reflected in one of the key working assumptions of U.S./Coalition forces: *insurgents will continue to target locations at which they have previously been successful until COIN actions force a change*.[48]

The central conclusion from this research is that just like patterns of urban crime, IED attacks also cluster in space and time:

> *H3:* Higher levels of insurgent activity are expected at or close to locations where attacks have previously been successful.

Research on Denial Policing

It is commonly expected that counterinsurgency (COIN) activities have a strong bearing upon both the location and the potential for diffusion of insurgent attacks. A number of important studies have addressed the impact of COIN on subsequent levels of insurgency but at an aggregate level and, thus, are unable to directly specify its local effects.[49] Empirical assessments of insurgent-COIN interaction at the local level are relatively few and far between due to a lack of data. In an attempt to redress this imbalance, Monica Duffy Toft and Yuri Zhukov distinguish between denial and punishment strategies of policing. "When implemented effectively, denial transforms the conflict zone into a closed system—insurgents are unable to flee to or reinforce operations from adjacent areas."[50] By contrast, punishment strategies are designed to impose pain to undermine insurgent resolve. In practical terms, denial is observed in efforts designed to restrict movement and to disrupt communication networks, including efforts to establish a cordon around a location. Punishment is measured in terms of kinetic force. Their conclusion, which chimes with that of the broader insurgency literature, is that denial is the preferred strategy to counter insurgency.[51]

To build upon a rich tradition of criminological research, Gary LaFree and co-authors have sought to explore the relevant deterrence and backlash models of policing. They do so in the case of British counterterrorism activities in Northern Ireland between 1969 and 1992. Their state-level analysis uncovers much stronger support for the idea of violent backlashes (rather than deterred activities) in response to counterterrorism activities.[52]

The ABM of Weidman and Salehyan suggests that early commitment of resources to COIN activity could enhance prospects for successful COIN.[53] This tentative conclusion chimes with the findings of Enterline and Greig who find that high numbers of troops devoted early in a COIN—what they characterize as the Shinseki Plan—is the most successful form of COIN.[54] Andrew Linke and colleagues use a space-time Granger causality technique to explore insurgent-coalition interaction for the period 2004–2009. For this they employ the Wikileaks datasets. They demonstrate strong reciprocal trends indicative of a "tit-for-tat" strategy on the part of insurgents.[55]

In a similar vein, using a novel extension of the Knox Test, Braithwaite and Johnson examine how space-time patterns of COIN activity affect those of IED attacks and vice versa. To better understand the interactions, rather than analyzing all forms of COIN action in the aggregate, they distinguish between those COIN actions that are targeted in nature and those that are less so. In contrast to the findings of Linke and colleagues, their analysis suggests that COIN operations closely follow the incidence of insurgent attacks but not vice-versa.[56]

Collectively, these extant studies and the notion of denial policing suggest a pair of competing hypotheses:

H4: Higher levels of insurgent activity are expected at or close to locations where COIN activities have previously been located (tit-for-tat).

Or:

H5: Lower levels of insurgent activity are expected at or close to locations where COIN activities have previously been located (denial policing).

Research Design

We have proposed five testable hypotheses reflecting expectations derived from the logics of three key Environmental Criminology approaches: risk heterogeneity, near repeat victimization, and denial policing. In this section we detail an appropriate research design to test these hypotheses on data characterizing levels of insurgent violence, COIN activities, and environmental characteristics at the local level in Baghdad at the peak of the Iraqi Insurgency in 2005.

Measuring Insurgency

Our dependent variable, "insurgent violence," includes details of 666 IED explosions that occurred in the area in and around Baghdad between January 1, 2005 and June 30, 2005. These data come from information reported to the Multi-National Force-Iraq (MNF-I) through daily Significant Activity (SIGACTs) reports. These data were made available by the Reconstruction Operations Center and whilst they are formally treated as "sensitive," they have been employed elsewhere in academic research. The data are geocoded to a resolution of 100 m (or better).[57] There is now a wealth of micro-level data (including aggregated versions of a more complete time series of SIGACTS data) available through the Empirical Studies of Conflict (ESOC) data project at Princeton University.[58] However, the ESOC collection includes details on the identity of the initiator and target only for the period April 2006 to September 2007 when the conflict was essentially an inter-ethnic conflict.[59] Thus, we opt to use the more fine-grained data covering the six months in 2005 that we feel best reflect the height of insurgent-COIN interactions.

Modeling Approach

In their assessment of space-time co-evolution of insurgent and counterinsurgent activities in Iraq, Braithwaite and Johnson use a novel extension to the Knox approach mentioned briefly above. To explain, in the case of the Knox Test, for a set of events, each observation is compared with every other and the distance and time between them calculated. A contingency table is then populated to summarize the distribution of event pairs that occur within particular space-time intervals of each other (e.g., within 1 km and 1 week of each other). The observed distribution is then compared with what would be expected, assuming the timing and location of events are independent. Instead of examining patterns for a single type of event—a univariate analysis—Braithwaite and Johnson use a bivariate approach to see how the timing and location of one set of events (IED attacks) is related to that of another (COIN action).[60]

The aim of the Knox Test is to estimate the extent to which events cluster in space *and* time above and beyond what would be expected, given that there is likely to be risk heterogeneity, whereby some locations will be more at risk of attacks than others. On the one hand, controlling for the influence of risk heterogeneity is a virtue of the test. On the other, doing so means that the explanatory contribution of specific (say) environmental factors cannot be estimated. A further related issue with the Knox approach is that the units of observation are the events of interest (e.g., IED attacks). Thus, the units of observation are not fixed in space and very different data-generating processes could lead to the same results. To illustrate, consider that if many events occurred near to each other in space and time and did so around the same fixed location in space, the same pattern would emerge in the contingency table as in the case where events occur near to each other in space and time but where there is a spatial drift in the locations where they occur.

As an alternative to this fluid framework, the majority of studies of violence of this kind in Iraq and Afghanistan choose to fix the spatial dimension of the unit of observation at either the district[61] or the neighborhood[62] level. However, whilst these reasonably reflect the scale at which Coalition COIN activity decisions may have been taken, it is not at all clear that this is a geography that influences or neatly contains insurgent behaviors. Accordingly, we opt to employ an alternative approach to analysis. Following a common practice in Environmental Criminology and an emerging trend in empirical studies of civil war,[63] we examine how the likelihood of events occurring at particular *fixed* locations varies over time. Specifically, we generate a fishnet that divides Baghdad into ($64^*54=$) 3,456 equally sized grid cell locations. This facilitates estimation of the contribution of time-stable factors (risk heterogeneity) and those that are dynamic (contagion). This consequently facilitates competitive testing of our five hypotheses.

Measuring Risk Heterogeneity

To test the implications of *H1* regarding the importance of opportunities in determining the heterogeneity of risks of attacks at the local level, we operationalize four independent variables. The first three of these characterize the density of different road types within the local grid cell. The first two represent counts of the number of "major roads" and "residential roads" within the local cell. The third then provides an interaction of these two: "major and residential roads." Data on the road network were obtained from the Open Street Map (OSM) database.[64] The available data identify the location of road network edges, and also differentiate between the different types of road link—thus allowing us to determine for each grid cell location whether or not it contains roads and of which type.

In addition, we generate a binary variable simply indicating whether the local grid cell intersects with a "military garrison." We digitized the location of the garrison established at the former Baghdad International Airport. We expect that cells containing a garrison are significantly less likely to experience insurgent attacks, because these are areas to which the Coalition committed significant levels of defensive forces and resources.

To test *H2*, we operationalize a measure of the density of the prevailing population within each of the local grid cells. Population data are not available at this local scale, thus we proxy population using estimates of the ambient population. These are obtained from the Oakridge National Laboratory (ORNL) Landscan database, which provides estimates for regular-sized cells of 1 km by 1 km for the entire world. This measure is captured using census data, remote sensing of land usage and cover, and nighttime visualization of levels of electrification. The spatial resolution at which these data are available is convenient in that it represents a meaningful scale of geography over which to study insurgent and COIN action. For this reason, we use the LandScan grid to define our unit of observation (as noted above).

Unfortunately, we do not have dynamic data on the whereabouts of different ethnic groups at this spatial scale. Data are available capturing the initial distribution of ethnic groups in parts of Baghdad—measured in 2003—to detail the influence of ethnicity upon the location of violence. However, when overlapped with our spatial scale, we lose a significant proportion of our observations. Accordingly, we opt not to include a measure of ethnic divisions.[65]

Measuring Space-Time Dynamics

To facilitate the modeling (for more detail, see below) of the influence of previous attacks and of those nearby (key elements of repeat victimization), we generate a three-dimensional matrix to represent the number of events that occur in each of the 64×54 cells for each of the 26 weeks for which we have data. From this, we generate a set of three pairs of spatial and temporal lag variables. We measure IED attacks at *t-1* and *t-2* at location *i*, as well as locations one and two grid cells removed from *i*, which we refer to as the first and second buffers. Evidence of near repeat victimization (and thus in support of *H3*) would take the form of positive coefficient estimates for these parameters.

Measuring COIN/Policing Activity

To test *H4* and *H5*, we operationalize measures of Coalition COIN activities. To explore the effects of denial policing, in particular, we create a variable that counts the number of cordon/search operations carried out in each cell at each time point. Our SIGACTs data include details on 373 such operations. We isolate cordon/search operations, in particular, because these are tactics employed with the specific goal of undermining insurgent capacity and, thus, are most reflective of strategies to deny. In particular, we operationalize these COIN activities in three pairs of spatial and temporal lags—replicating our approach for the test of *H3* (discussed above). Thus we have counts of cordon/search events at *t*, *t-1*, and *t-2* for grid cell_i, and its first and second ring of buffer cells.

Model Specification

The equation below shows the model used in the case where current IED attacks are used to predict future occurrences of IED attacks. The first two sets of terms are time-lagged variables that are used to model the diffusion of risk from within the same cell and the set of adjacent (buffer) cells. Rather than modeling diffusion from only the immediately neighbouring cells, we do so for the first- and second-order neighbours. Similarly, rather than assuming that the likelihood of events will be influenced by what happened last week, we include two temporal lags in the model. The model is easily extended to include additional terms for other types of events, such as COIN activity—for which we also include a set of spatial and temporal lag terms as detailed above. The remaining terms represent those factors included in our model that vary over space but that are time-invariant, such as the ambient population and the configuration of the street network. Of course, for any such model there will be numerous omitted variables. Some of these will vary for known geographic areas, whereas for others, how their influence varies spatially will be unknown. To try to capture some of the effects of the former—so that their influence is not confused with the influences of those factors that are explicitly modeled—we include fixed effects terms for the nine districts in Baghdad. Accordingly, we end up with a model specified as follows:

$$Cell_{i,j,t} = \sum_{a=1}^{2} \beta\ Cell_{i,j,t-a} + \sum_{a=1}^{2}\sum_{b=1}^{2} \frac{1}{b.8} \beta\ Buffer_{b,t-a} + \beta AmbientPop_{i,j}$$
$$+ \sum_{n=1}^{10} \beta\ District_{i,j,n} + \sum_{R=1}^{3} \beta Road_{i,j,R} + \beta Garrison_{i,j} + \varepsilon_{i,j,t}$$

Where,

- $\text{Cell}_{i,j,t}$ is the dependent variable to be modeled and is a binary indicator of whether or not an IED attack occurred in cell_i in week t (where t varies from 1 to 26);
- $\text{Cell}_{i,j,t\text{-}a}$ is an independent variable that represents the time-lagged count of events of a particular type in cell_i in week $t\text{-}a$ (where a varies from 1 to 2);

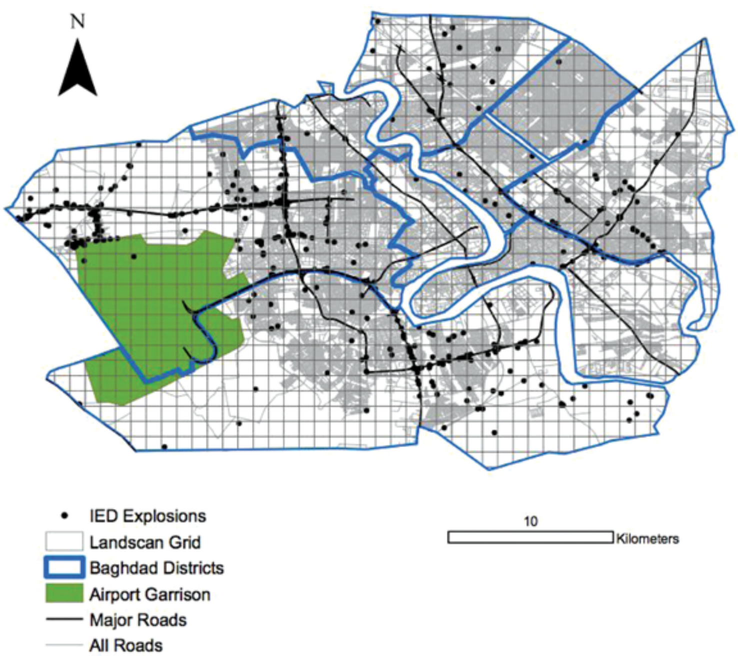

Figure 1. Map of IED explosions and key covariates across Baghdad, January to June, 2005 (road data acquired from OpenStreetMap).

- $\text{Buffer}_{i,j,t\text{-}a}$ is an independent variable that represents the space-time lagged count of events of a particular type in a buffer_b in week *t-a* (where a varies from 1 to 2);
- Ambient Pop is the LandScan estimate of the ambient population for a given cell;
- The Road variables are a set of binary variables that indicate whether there is a road of each type *R* in cell_i (where roads are classified as either residential or major roads);
- Garrison is a binary variable that indicates whether cell_i is located within an area that is part of a military garrison;
- The District variables are a set of binary variables, one for each of nine districts (minus a reference category), that indicate the geographic district within which cell_i is located;
- The βs are coefficients estimated using maximum likelihood methods—specifically, a logistic regression; and
- $\varepsilon_{i,t}$ is the residual error term.

The distribution of some of the key elements of this model specification is visualized in the map in Figure 1. This map, which covers the whole of Baghdad, identifies the point locations of the 666 IED explosions recorded within this area between June and January 2005. The map also depicts (in order on the legend) the 1 km × 1 km grid used in the analyses, the nine districts of Baghdad, the airport garrison, and the major and residential (all) roads.

Results

Table 1 details the results of four logistic regression models exploring the likelihood of observing at least one IED attack at a locale in a particular week. This binary outcome is modeled, respectively, as a product of factors characterizing risk heterogeneity (Model 1), near repeat victimization (Model 2), and denial policing (Model 3) approaches. Model 4 then combines each set of covariates in a full specification.

Model 1 shows that each of our indicators of risk heterogeneity significantly predicts which cells will include some IED attacks. Insurgents very clearly target locations with high levels of population and road infrastructure coverage, and appear to avoid the airport garrison more than would be expected on a chance basis. These findings are in line with our expectations.

Model 2 identifies strong evidence of escalatory and contagious process consistent with the logic of (near) repeat victimization. Prior levels of attacks (at both *t-1* and *t-2*) both at the same location and nearby strongly predict the occurrence of IEDs at cell_i in the current period_t.

Model 3 returns consistently positive coefficient estimates on the parameters measuring cordon/search activities in cell_i and nearby locations over the previous two time periods. The levels of statistical significance are not consistent across each of these parameters, however, suggesting that the effects are not equal at different spatial and temporal scales. In fact, and in contrast to the pattern observed for IED attacks, the effect appears to be strongest for COIN operations that occurred in the second spatial buffer two weeks prior to the period of interest. This provides some evidence that is consistent with tit-for-tat accounts, but may also suggest that rather than completely suppressing insurgent activity, denial policing might instead relocate or displace it to nearby locations.

Table 1. The effect of risk heterogeneity, repeat victimization, and denial policing on the local incidence of IED attacks

	1 Risk heterogeneity	2 Near repeat victimization	3 Denial policing	4 Full model
Ambient population (per 1000)	1.04*** (3.91)			1.04*** (4.13)
Major roads	8.21*** (18.69)			7.11*** (16.59)
Residential roads	1.67*** (3.48)			1.47*** (2.37)
Major and residential roads	8.99*** (15.60)			5.93*** (11.67)
Airport Garrison	0.04*** (−3.22)			0.07*** (−2.66)
Same location				
IED t-1		3.43*** (10.11)		2.39*** (6.95)
IED t-2		3.11*** (8.89)		2.01*** (5.54)
Cordon t-1			1.73*** (2.97)	1.57* (2.35)
Cordon t-2			1.15 (0.59)	1.11 (0.41)
Buffer 1 location				
IED t-1		26.61*** (7.59)		13.52*** (6.98)
IED t-2		12.83*** (8.89)		6.68*** (5.54)
Cordon t-1			2.05 (1.05)	0.74 (−0.39)
Cordon t-2			3.88*** (2.07)	2.31 (1.19)
Buffer 2 location				
IED t-1		6.37*** (2.43)		1.96 (0.86)
IED t-2		10.47*** (3.16)		2.91 (1.41)
Cordon t-1			11.40*** (2.49)	1.14 (0.12)
Cordon t-2			41.47*** (3.99)	13.22** (2.57)
District fixed effects	Yes	Yes	Yes	Yes
Constant	0.00	0.01	0.00	0.00
AIC	5734	5956	6321	5538

Note: Logistic regression models with $e\beta$, z-scores in parentheses.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Finally, Model 4 offers a competitive test of each of these models. Here we can assess both the changes in individual parameter estimates (as compared to themselves in Models 1 to 3), as well as the Akaike information criterion (AIC) summary of model fit. In the first instance, we can clearly see that the risk heterogeneity parameters remain strongly significant as predictors of IED attacks. At the same time, the second buffer parameters lose statistical significance, suggesting that patterns of near repeat victimization are much more contained spatially. Finally, we see that all but two of the COIN parameter estimates largely lose statistical significance. These general observations are reinforced by the AIC estimates. The AIC provides a means of judging the relative explanatory power of the different models. In particular, it provides a means of judging that balances between the goodness of fit of the model to the underlying data-generating process and the complexity of the model (the number of parameters therein). In this instance, the AIC shows us that whilst the full model performs best, it is only marginally better than the notably more parsimonious risk heterogeneity model.

Discussion and Conclusion

This article was motivated by a desire to uncover whether variation in the local characteristics of places, counterinsurgency (COIN) activities, or local contagion effects most notably influence where insurgent attacks occur. We developed a simple set of four logistic regression models to test five hypotheses reflecting three prominent perspectives from Environmental Criminology: "risk heterogeneity," "near repeat victimization," and "denial policing."

Our models suggest a consistent influence of the first two. By contrast, however, we highlight a much weaker role for prior COIN activities in determining where insurgency occurs. This may well be because COIN activities have neither or both of the effects hypothesized; that is to say that they may both reduce insurgent opportunities to attack (the expectation of denial policing logics) whilst also increasing the desire to do so (the expectation of tit-for-tat logics). Additionally, we note that the association observed might suggest that COIN activity does not entirely suppress or directly encourage it but instead might displace their activity geographically. In the case of urban crime, the best available evidence[66] suggests that policing and other geographically focused crime prevention activities do not typically displace criminal activity spatially. Possible explanations for this finding articulated in the literature are that criminals have limited activity spaces and so are deterred when local opportunities are blocked, and that opportunities for crime are not uniformly distributed in the environment, meaning that when one opportunity is removed, alternatives may not exist nearby and so offending is reduced. In the case of insurgency, the actors involved may be more motivated to seek out alternative targets, and while target attractiveness may vary, there may be many possible locations that would be suitable for IED attacks, meaning that some forms of COIN action, particularly perhaps that which is acutely focused geographically, may simply relocate insurgent activity to localities nearby.

These findings are very much preliminary at this stage. Nonetheless, they suggest that insurgency displays similar patterns at the local level as civil wars more broadly display at the national and regional level.[67] Future work might aim to examine the extent to which the micro-level patterns observed here are apparent for other forms of political violence using a similar approach to that described here. It might also build on the work reported here to develop forecasting models intended to predict where further IED attacks are most likely. As with research concerned with urban crime, such models might differentiate between long-term[68] and short-term[69] predictions to inform different COIN strategies. Our statistical model includes parameters that estimate the influence of time-stable factors and those that are more dynamic, such as the timing and location of recent attacks. We suggest that the inclusion of both types of influence would be a sensible way forward in the development of forecasting models intended to predict where events are most likely to happen next, where next might be the next day or week. Models intended to predict longer-term trends may emphasize the role of recent activity somewhat less, perhaps focusing more on characteristics of the environment to identify risky places. What factors best predict the timing and location of future attacks is, of course, an empirical question and we hope that future research will explore this issue.

One weakness of the approach reported here (and elsewhere), is that while heterogeneity is considered in terms of environmental influences, the underlying processes that drive observed patterns are essentially assumed to be homogeneous. To explain, consider that in one area an IED attack or COIN activity might encourage further insurgent activity. However, in another area, the outcome might be rather different, with insurgent activity being suppressed. If such variation exists, it may be random insofar as it is not possible to identify regularities in observed patterns. However, there may be systematic differences in the extent to which particular outcomes are triggered by one action or another. Similarly, there may be systematic differences as far as when one outcome is more likely than another. For instance, insurgents are unlikely to target the exact same locations infinitely as there would be little left to target and the risk of capture or disruption will increase over time. Hence, the relationship between the event history at a location and changes in the probability of further attacks may be non-linear, with the likelihood of attacks initially increasing, but subsequently decreasing when the benefits of so doing decline and the risks increase to unacceptable levels. Some of the challenges for future research will be to articulate theoretical expectations as to how and why such mechanisms might vary over space and time, and to then test them empirically.

The data analyzed here represent a sample of that recorded by the military. As such, it is unlikely to provide a complete picture and there will be some bias in terms of what is recorded and what is not. Given that the data are used to inform military action, we have no reason to suspect that data will be omitted systematically. There is no way of objectively assessing the extent of such bias and the same issues are, of course, associated with any studies that rely on secondary sources of data (institutional or open source), whether they be studies of crime[70] or insurgency.[71] It is important to acknowledge the potential limitations of the data.

Another issue concerns the units of analysis. Here we analyze patterns observed for 1 km by 1 km grid cells. This was partly because this was the lowest level of resolution at which data regarding the ambient population were available, but also because this seemed a meaningful spatial scale (i.e., we could have aggregated the data to larger areal units). However, it is well known that different outcomes may be observed for analyses conducted using different areal units[72] and this should be borne in mind. That said, the choice of areal unit selected here, we argue, is both meaningful theoretically and practically—perhaps the two most important considerations that should guide the selection of units of analysis.

Future research could also look to further explore patterns of violence on specific road segments. Some prior research exists that demonstrates that road ends, such as cul-de-sacs and dead ends, are especially prone to IED attacks. In that study, the researchers suggested that this is likely due to these locations exposing COIN convoy vulnerabilities.[73] Furthermore, it could prove worthwhile to assess the impact of demographic heterogeneity as it maps onto road and neighborhood networks. Anecdotal evidence suggests, for instance, that the edges between different ethnic neighborhoods attracted a lot of sectarian violence in Baghdad.[74]

To conclude, the current study provides further evidence that IED attacks are not randomly distributed geographically and tests a series of hypotheses as to why this is the case. It demonstrates that risk heterogeneity, near repeat victimization, and denial policing approaches from Environmental Criminology each contribute to our understanding of the observed space-time clustering of IED attacks. Of these explanations, however, it appears that in the current case, risk heterogeneity is particularly important. Finally, the study supports the suggestion that research concerning insurgency and terrorism more broadly could benefit from considerations of the contribution of environmental criminological theories and empirical approaches to analysis.

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Notes

1. Our analytical focus in this article is on insurgent violence. However, we draw upon a great deal of research into patterns of terrorist violence. We consider the primary difference between insurgent and terrorist violence as being their most common targets: military and public actors, respectively. The data that we bring to bear in this study are most accurately to be treated as evidence of insurgency (as we discuss further below). However, we feel that the factors determining these non-state actor uses of force are likely to parallel those in place in the processes of terrorism.

2. Nils B. Weidmann and Idean Salehyan, "Violence and Ethnic Segregation: A Computational Model Applied to Baghdad," *International Studies Quarterly* 57 (2013): 52–64.

3. Manus I. Midlarsky, Martha Crenshaw, and F. Yoshida, "Why Violence Spreads: The Contagion of International Terrorism," *International Studies Quarterly* 24 (1980): 262–298.

4. See, for instance, Shane D. Johnson, Kate Bowers, and A. Hirschfield, "New Insights into the Spatial and Temporal Distribution of Repeat Victimisation," *The British Journal of Criminology* 37, no. 2 (1997): 224–244.

5. Shane D. Johnson and Kate Bowers, "The Stability of Space-Time Clusters of Burglary," *British Journal of Criminology* 44, no. 1 (2004): 55–65; Shane D. Johnson, Wim

Bernasco, Kate Bowers, Henk Elffers, Jerry Ratcliffe, George Rengert, and Michael Townsley, "Space Time Patterns of Risk: A Cross National Assessment of Residential Burglary Victimization," *Journal of Quantitative Criminology* 23 (2007): 201–219.

6. See, for instance, Johnson and Bowers, "The Stability of Space-Time Clusters of Burglary" (see note 5 above); Shane Johnson, Lucia Summers, and Ken Pease, "Offender as Forager? A Direct Test of the Boost Account of Victimization," *Journal of Quantitative Criminology* 25 (2009): 181–200.

7. See, for instance, Sebastian Schutte and Nils B. Weidmann, "Diffusion Patterns of Violence in Civil Wars," *Political Geography* 30, no. 3 (2011); Weidmann and Salehyan, "Violence and Ethnic Segregation" (see note 2 above); Monica Duffy Toft and Yuri Zhukov, "Denial and Punishment in the North Caucasus: Evaluating the Effectiveness of Coercive Counter-insurgency," *Journal of Peace Research* 49, no. 6 (2012): 785–800.

8. Ken Pease, *Repeat Victimisation: Taking Stock*, Crime Prevention and Detection Series, Paper 90 (London: Home Office, 1998).

9. This concept acts essentially as the null hypothesis in the recent study of civil conflict contagion by Halvard Buhaug and Kristian Skrede Gleditsch, "Contagion or Confusion? Why Conflicts Cluster in Space," *International Studies Quarterly* 52, no. 2 (2008): 215–233.

10. See, for instance, Trevor Bennett and Richard Wright, *Burglars on Burglary: Prevention and the Offender* (Brookfield, VT: Avebury Publishing, 1984).

11. See, for instance, Shane D. Johnson, "Repeat Burglary Victimization: A Tale of Two Theories," *Journal of Experimental Criminology* 4 (2008): 215–240; Ashley Pitcher and Shane D. Johnson, "Examining Theories of Victimization Using a Mathematical Model," *Journal of Research in Crime and Delinquency* 1 (2011): 83–109.

12. Benjamin A. Most and Harvey Starr, *Inquiry, Logic, and International Politics* (Columbia: University of South Carolina Press, 1989).

13. "More Attacks, Mounting Casualties," *Washington Post*, September 30, 2007, http://www.washingtonpost.com/wp-dyn/content/graphic/2007/09/28/GR2007092802161.html

14. Yuri Zhukov, "Roads and the Diffusion of Insurgent Violence," *Political Geography* 31, no. 3 (2012): 144–156.

15. "Cell-phone Technology and Explosive Tool for Insurgents," *Washington Times*, March 7, 2005, http://www.washingtontimes.com/news/2005/mar/7/20050307-121323-4533r/?page=1.

16. Jacob N. Shapiro and Nils B. Weidman, "Is the Phone Mightier than the Sword? Cell Phones and Insurgent Violence in Iraq," Working Paper (Princeton, NJ: Princeton University).

17. John Agnew, Thomas Gillespie, Jorge Gonzalez, and Brian Min, "Baghdad Nights: Evaluating the US Military 'Surge' Using Nighttime Light Signatures," *Environment and Planning A* 40 (2008): 2285–2295.

18. Weidmann and Salehyan, "Violence and Ethnic Segregation" (see note 2 above).

19. See, for instance, Agnew et al., "Baghdad Nights" (see note 17 above).

20. Stathis Kalyvas and Matthew Adam Kocher, "Ethnic Cleavages and Irregular War: Iraq and Vietnam," *Politics & Society* 35, no. 2 (2007): 183–223.

21. See, for instance, John O'Loughlin and Frank Witmer, "The Localized Geographies of Violence in the North Caucasus of Russia, 1999–2007," *Annals of the Association of American Geographers* 101, no. 1 (2010): 178–201; John O'Loughlin, Frank Witmer, and Andrew Linke, "The Afghanistan-Pakistan Wars 2008–2009: Micro-Geographies, Conflict Diffusion, and Clusters of Violence," *Eurasian Geography and Economics* 51, no. 4 (2010): 437–471.

22. Adolphe Quetelet, *Research on the Propensity for Crime at Different Ages*, trans. S. F. Sylvester (Cincinnati: Anderson Publishing, 1984). Original work published in 1831.

23. See, for instance, Clifford R. Shaw and Henry D. McKay, *Juvenile Delinquency and Urban Areas* (Chicago: University of Chicago Press, 1969).

24. See, for instance, Shane D. Johnson and Kate J. Bowers, "Permeability and Crime Risk: Are Cul-de-Sacs Safer?," *Journal of Quantitative Criminology* 26, no. 1 (2010): 89–111; Elizabeth R. Groff, David Weisband, and Sue-Ming Yang, "Is it Important to Examine Crime Trends at a Local 'Micro' Level?: A Longitudinal Analysis of Street to Street Variability in Crime Trajectories," *Journal of Quantitative Criminology* 26, no. 1 (2010): 7–32.

25. Pease, "Repeat Victimisation" (see note 8 above).

26. John E. Eck, Ronald V. Clarke, and Rob T. Guerette, "Risky Facilities: Crime Concentration in Homogenous Sets of Establishments and Facilities," *Crime Prevention Studies* 21 (2007): 225–264.

27. Lawrence E. Cohen and Marcus Felson, "Social Change and Crime Rate Trends: A Routine Activity Approach," *American Sociological Review* 44, no. 4 (1979): 588–608.

28. See, for instance, Shane Johnson, "A Brief History of the Analysis of Crime Concentration," *European Journal of Applied Mathematics* 21, nos. 4–5 (2010): 349–370.

29. Johnson, "Repeat Burglary Victimization" (see note 11 above).

30. Johnson et al., "New Insights into the Spatial and Temporal Distribution of Repeat Victimisation" (see note 4 above).

31. See, for instance, Julie Ashton, Imogen Brown, Barbara Senior, Ken Pease, "Repeat Victimization: Offender Accounts," *International Journal of Risk Security and Crime Prevention* 3, no. 4 (1998): 269–279; Lucia Summers, Shane D. Johnson, and George Rengert, "The Use of Maps in Offender Interviews," in Wim Bernasco, ed., *Offenders on Offending: Learning About Crime from Criminals* (Cullompton: Willan, 2010), 246–272.

32. See, for instance, Steve Everson and Ken Pease, "Crime Against the Same Person and Place: Detection Opportunity and Offender Targeting," *Crime Prevention Studies* 12 (2001): 199–220; Edward R. Kleemans, "Repeat Burglary Victimization: Results of Empirical Research in the Netherlands," *Crime Prevention Studies* 12 (2001): 53–68; Wim Bernasco, "Them Again: Same-Offender Involvement in Repeat and Near Repeat Burglaries," *European Journal of* Criminology 5, no. 4 (2008): 411–431; Johnson et al., "Offender as Forager?" (see note 6 above).

33. See, for instance, Johnson and Bowers, "The Stability of Space-Time Clusters of Burglary" (note 5 above); Johnson et al., "Space Time Patterns of Risk" (see note 5 above); Johnson et al., "Offender as Forager?" (see note 6 above).

34. Waldo R. Tobler, "A Computer Movie Stimulating Urban Growth in the Detroit Region," *Economic Geography* 46 (1970): 234–240.

35. Kate Bowers and Shane Johnson, "Domestic Burglary Repeats and Space-Time Clusters: The Dimension of Risk," *European Journal of Criminology* 2 (2005): 67–92; Johnson et al., 2007; M. Townsley, R. Homel and J. Chaseling, "Infectious Burglaries. A Test of the Near Repeat Hypothesis," *British Journal of Criminology* 43, no. 3 (2003): 615–633.

36. Johnson et al., "Space Time Patterns of Risk" (see note 5 above).

37. Summers et al., "The Use of Maps in Offender Interviews" (see note 31 above).

38. Bernasco, *Offenders on Offending* (see note 31 above); Johnson et al., "Offender as Forager?" (see note 6 above).

39. Pitcher and Johnson, "Examining Theories of Victimization Using a Mathematical Model" (see note 11 above).

40. See, for example, George Knox, "Epidemiology of Childhood Leukemia in Northumberland and Durham," *British Journal of Preventive Social Medicine* 18 (1964): 17–24; Julian Besag and Peter J. Diggle, "Simple Monte Carlo Tests for Spatial Pattern," *Applied Statistics* 26 (1977): 327–333.

41. See, for instance, Johnson and Bowers, "The Stability of Space-Time Clusters of Burglary" (see note 5 above); Bowers and Johnson, "Domestic Burglary Repeats and Space-Time Clusters" (see note 35 above).

42. Johnson et al., "Offender as Forager?" (see note 6 above); Jerry H. Ratcliffe and George F. Rengert, "Near-repeat Patterns in Philadelphia Shootings," *Security Journal* 21 (2008): 58–76.

43. Johnson, "Repeat Burglary Victimization" (see note 11 above).

44. Pitcher and Johnson, "Examining Theories of Victimization Using a Mathematical Model" (see note 11 above).

45. Michael T. Townsley, Shane D. Johnson, and Jerry R. Ratcliffe, "Space-Time Dynamics of Insurgent Activity," *Security Journal*, 21, no. 3 (2008): 139–146; Shane D. Johnson and Alex Braithwaite, "Spatio-Temporal Modeling of Insurgency in Iraq," *Crime Prevention Studies* 25 (2009): 9–32; Alex Braithwaite and Shane D. Johnson, "Space-Time Modeling of Insurgency and Counter-Insurgency in Iraq," *Journal of Quantitative Criminology* 28, no. 1 (2012): 31–48; Gary LaFree, Laura Dugan, Min Xie, and Piyusha Singh, "Spatial and Temporal Patterns of Terrorist Attacks by ETA 1970 to 2007," *Journal of Quantitative Criminology* 28, no. 1 (2011): 7–29.

46. Brandon Behlendorf, Gary LaFree, and Richard Legault, "Microcycles of Violence: Evidence from Terrorist Attacks by ETA and the FMLN," *Journal of Quantitative Criminology* 28, no. 1 (2012): 49–75.

47. Johnson and Braithwaite, "Spatio-Temporal Modeling of Insurgency in Iraq" (see note 45 above).

48. Department of the Army, Headquarters, *Combined Arms Improvised Explosive Device Defeat Operations* (FM 3-90.119/MCIP 3-17.01), 2007, http://www.us.army.mil

49. Matthew Adam Kocher, Thomas B. Pepinsky, and Stathis N. Kalyvas, "Aerial Bombing and Counterinsurgency in the Vietnam War," *American Journal of Political Science* 55, no. 2 (2011): 201–218; Jason Lyall, "Does Indiscriminate Violence Incite Insurgent Attacks? Evidence from Chechnya," *Journal of Conflict Resolution* 53, no. 2 (2009): 331–362.

50. Toft and Zhukov, "Denial and Punishment in the North Caucasus" (see note 7 above).

51. David Galula, *Pacification in Algeria 1956–1958*, MG-478-1. (Santa Monica, CA: RAND, 1963); Ivan Arreguin-Toft, "How the Weak Win Wars: A Theory of Asymmetric Conflict," *International Security* 26, no. 1 (2001): 93–128; Ivan Arreguin-Toft, *How the Weak Win Wars: A Theory of Asymmetric Conflict* (New York: Cambridge University Press, 2005).

52. Gary LaFree, Laura Dugan, and Raven Korte, "The Impact of British Counterterrorist Strategies on Political Violence in Northern Ireland: Comparing Deterrence and Backlash Models," *Criminology* 47, no. 1 (2009): 17–45.

53. Weidmann and Salehyan, "Violence and Ethnic Segregation" (see note 2 above).

54. Andrew J. Enterline and Michael J. Greig, "Surge, Escalate, Withdraw, and Shinseki: Forecasting and Retro-Casting American Force Strategies and Insurgency in Iraq," *International Studies Perspectives* 8, no. 3 (2007): 245–252.

55. Andrew Linke, Frank Wittmer, and John O'Loughlin, "Space-Time Granger Analysis of the War in Iraq: A Study of Coalition and Insurgent Action-Reaction," *International Interactions* 38, no. 4 (2012): 402–425.

56. Braithwaite and Johnson, "Space-Time Modeling of Insurgency and Counter-Insurgency in Iraq" (see note 45 above).

57. A more complete discussion of these data is available from Johnson and Braithwaite, "Spatio-Temporal Modeling of Insurgency in Iraq" (see note 45 above) and Braithwaite and Johnson, "Space-Time Modeling of Insurgency and Counter-Insurgency in Iraq" (see note 45 above).

58. Details are available online at: http://esoc.princeton.edu.

59. Weidmann and Salehyan, "Violence and Ethnic Segregation" (see note 2 above).

60. Johnson and Braithwaite, "Spatio-Temporal Modeling of Insurgency in Iraq" (see note 45 above).

61. See, for instance, Agnew et al., "Baghdad Nights" (see note 17 above) and Shapiro and Weidman, "Is the Phone Mightier than the Sword?" (see note 16 above).

62. Weidmann and Salehyan, "Violence and Ethnic Segregation" (see note 2 above).

63. Halvard Buhaug, Kristian S. Gleditsch, Helge Holtermann, Gudrun Ostby, and Andreas F. Tollefsen, "It's the Local Economy, Stupid! Geographic Wealth Dispersion and Conflict Outbreak Location," *Journal of Conflict Resolution* 55, no. 5 (2011): 814–840; Andreas F. Tollefsen, Havard Strand, and Halvard Buhaug, "PRIO-GRID: A Unified Spatial Data Structure," *Journal of Peace Research* 49, no. 2 (2012): 363–374.

64. The Open Street Maps data are available online at: http://www.openstreetmap.org

65. These data are used by Weidman and Salehyan, "Violence and Ethnic Segregation" (see note 2 above) and were georeferenced from the work of Izady at Columbia University.

66. Kate Bowers, Shane D. Johnson, Rob T. Guerrette, Lucia Summers, and Suzanne Poynton, "Spatial Displacement and Diffusion of Benefits Among Geographically Focused Policing Initiatives: A Meta-Analytical Review," *Journal of Experimental Criminology* 7, no. 4 (2011): 347–374; Shane D. Johnson, Kate J. Bowers, and Rob T. Guerrette, "Crime Displacement and Diffusion of Benefits: A Review of Situational Crime Prevention Measures," in Brandon C. Welsh and David P. Farrington, eds., *The Oxford Handbook of Crime Prevention* (Oxford: Oxford University Press, 2012), 337–353.

67. That is, we find a role for both spatial heterogeneity and dependence in explaining the local incidence of clusters of attacks. This is in line with the finding of Buhaug and Gleditsch, "Contagion or Confusion" (see note 9 above).

68. Shane D. Johnson, Stephen P. Lab, and Kate J. Bowers, ‘‘The Stability of Crime Hotspots: Identification and Differentiation,’’ *Built Environment* 34, no. 1 (2008): 32–45.

69. Shane D. Johnson, Kate J. Bowers, Dan J. Birks, and Ken Pease, ‘‘Predictive Mapping of Crime by ProMap: Accuracy, Units of Analysis and the Environmental Backcloth,’’ in David Weisburd, Wim Bernasco, and Gerben J. N. Bruinsma, eds., *Putting Crime in its Place: Units of Analysis in Spatial Crime Research* (New York: Springer, 2008), 171–198; Shane D. Johnson, Dan J. Birks, Lindsey McLaughlin, Kate J. Bowers, and Ken Pease, *Prospective Mapping in Operational Context, Home Office Online Report 19/07* (London: Home Office, 2007); Kate J. Bowers, Shane D. Johnson, and Ken Pease, ‘‘Prospective Hot-spotting: The Future of Crime Mapping?’’ *The British Journal of Criminology* 44, no. 5 (2004): 641–658; George Mohler, Martin B. Short, P. Jeffrey Brantingham, Frederic P. Schoenberg, and George Tita, ‘‘Self-exciting Point Process Modeling of Crime,’’ *Journal of the American Statistical Association* 106 (2011): 100–108.

70. For a discussion, see Mike Maguire, ‘‘Criminal Statistics and the Construction of Crime,’’ in Mike Maguire, Rod Morgan, and Robert Reiner, eds., *The Oxford Handbook of Criminology* (Oxford: Oxford University Press, 2012), 206–224.

71. For a discussion, see Gary LaFree, ‘‘The Global Terrorism Database: Accomplishments and Challenges,’’ *Perspectives on Terrorism: A Journal of the Terrorism Research Initiative* 4, no. 1 (2010): 24–46.

72. Stanley Openshaw, ‘‘The Modifiable Areal Unit Problem,’’ *Concepts and Techniques in Modern Geography* 38 (1984): 41.

73. Sven A. Brueckner, ‘‘Swarming Geographic Event Profiling, Link Analysis, and Prediction’’ (Paper presented at the 3rd International Conference on Self-Adaptive and Self-Organizing Systems, San Francisco, CA, September 2009).

74. We are grateful to a reviewer for offering these suggestions.