The Peace Dividend of Distance: Violence as Interaction Across Space*

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Abstract

More distant targets are harder to attack, and hence increased distance between potential attackers and targets may reduce fatalities. To study this, we model violence as interaction across space, using a game-theoretic model. To estimate the structural parameters of the model, we use fine-grained data from Northern Ireland on local religious composition, and on the identity of attackers and victims in violent events in 1969-1989. Quantifying the effect of distance adds dramatically to our understanding of where violence arises in a conflict. Our model also predicts the trajectory of attacks, the construction of so-called "peacewalls" and suggests that changing distances due to population movements can account for a large part of the drop in violence in the 1980s.

Keywords: Conflict, Ethnic Violence, Religious Violence, Spatial Data, Distance Costs, Polarization, Segregation, Northern Ireland, Insurgency.

JEL Classification: D74, K42, N44, Z10.

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1 Introduction

Interactions between people are typically easier, and hence more intense and frequent, when they are geographically close. This decay of interaction with increasing distance has been found to be relevant for various fields in economics. For example, trade economists refer to "iceberg trade costs" increasing in distance and use "gravity models of trade" to account for the fact that trade between more distant places is more costly.[1] Similarly, textbook models of monopolistic competition have distance costs built into their very core. Consumer demand for all kinds of products has been shown to be decreasing in distance. But distance decay is not restricted to benevolent interactions. Criminologists have found that criminals more frequently commit crimes closer to home, allowing the computation of "distance-decay functions of crime". Empirical studies in economics suggest that distance to potential offenders may reduce risk.[2] It seems therefore obvious that geographical distance between actors should also matter for armed conflict. This is especially true in civil conflict where different parts of the population attack each other. Yet, theoretical research which separates the location of attackers and targets and models their interaction in space is extremely scarce.

The purpose of the current paper is to offer a model of violence as a spatial interaction. As a starting point for our model of civil war we assume that attackers have a base for their operation and that an attack's success rate decays with distance to this base.[3] In the model we show that, under some additional assumptions, the expected origins of attacks can be backed out from the spatial distributions of casualties and population. We also show that our theory of conflict provides new insights when compared to existing theoretical concepts such as ethnic polarization or segregation or tools such as spatial econometrics models (see section 2).

[1] For theoretical foundation see Anderson (1979). For an excellent review see Behar and Venables (2011).

[2] See, for example, Linden and Rockoff (2008) who show that house prices fall significantly when registered sex offenders move into a neighbourhood.

[3] In civil wars these bases are typically located in neighborhoods which support the attackers through e.g. personnel, logistics and, crucially, information provision.

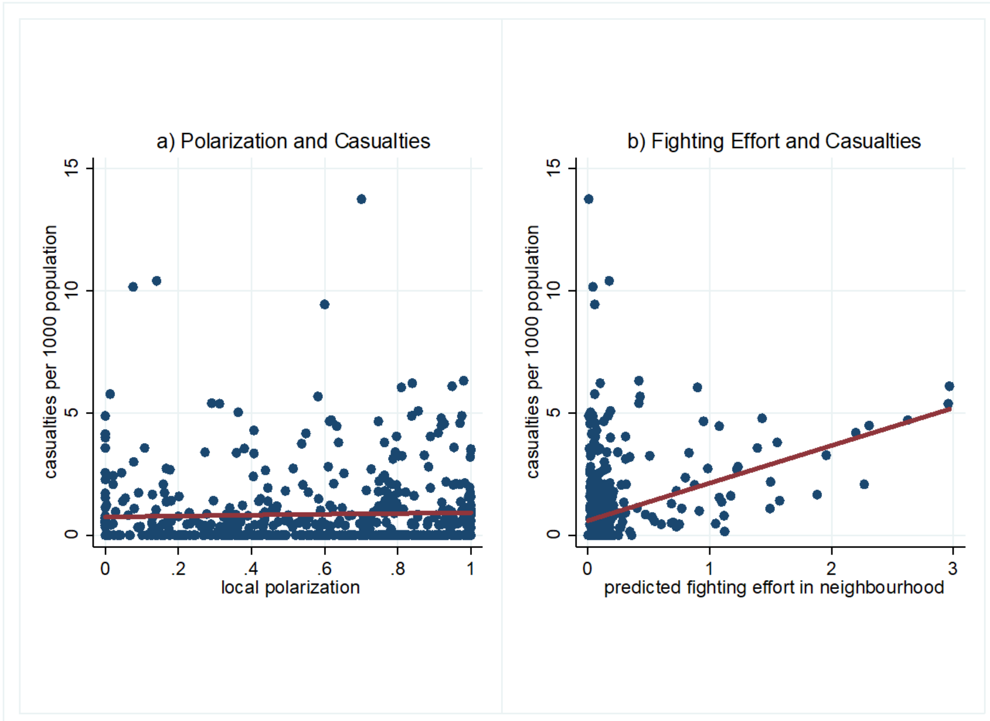
We further apply our model to novel, fine-grained data on the religious dimension of the Northern Irish conflict. Northern Ireland –being a rare example of a developed country experiencing an intense conflict– provides a unique setting that allows us to match detailed conflict events and location data with fine-grained census data on the exact number of members from different religious groups in 582 local administrative wards.

Figure 1, Panel a) illustrates a classic approach towards this data which follows the literature on ethnic polarization applied to the micro level. On the x-axis we show the polarization score in each of the 582 wards of Northern Ireland and on the y-axis we display the number of casualties per 1000 population in each of the wards.[4] There is no discernable association between polarization on the ward level and casualties.

This motivates the development of our theory targeted at explaining patterns of violence at the micro level. Our data together with the model allows us to estimate the distribution of violence in space. We find that violence observed in a given ward can be explained by the spatial interaction of different populations, and that increasing the distance between potential perpetrators and targets has a quantitatively important effect of reducing violence. In particular, for a given level of fighting motivation, an interaction within ward is 2 to 6 times more dangerous than between wards. The results are shown to be robust to a variety of alternative assumptions, alternative samples and alternative treatment of standard errors. A placebo test is also carried out.

A truly spatial model of the interaction in conflict offers large advantages when predicting the location of attacks compared to other models. Figure 1, Panel b) shares the same y-axis with Figure 1, Panel a) but plots on the x-axis our estimate of fighting effort which is derived from the same population data but based on our micro-founded theory. The positive association with casualties per capita is clearly visible in the Figure.

[4] To construct Figure 1 we have used population numbers from the 1971 census (NISRA, 2015) and casualties from Sutton (1994) and CAIN (2015). The polarization formula is discussed in detail in Montalvo and Reynal-Querol (2005).



Note: Local polarization is given by: share of Catholics * share of Protestants at the ward level * 4. Fighting effort is a measure derived from the number of Catholics and Protestants in the ward and neighbouring wards: F in equation (2). The slope coefficient in Figure a) is -.12 with a t-stat of 0.33 and the slope coefficient in Figure b) is 1.48 with a t-stat of 9.76.

Figure 1: Understanding Casualties at the Local Level

The explanatory power of the theory is a first, clear advantage of introducing quantitative estimates of the effect of distance into a standard model of violence. Yet, our model also permits us to estimate the origin and, hence, path taken by attacks. We illustrate this by using the model to generate a ward-by-ward analysis of the predicted number of attacks across each ward boundary. We compare our predictions with the actual placement of barriers by the UK government. It turns out that we can predict well the placement of these "peace walls" using the expected extent of violence that travels through a location. We use ward fixed effects at origin and destination to show that it is the interaction across space, and not ward characteristics per se, that drives the placement of walls on specific boundaries of a ward.

Finally, our estimates allow us to study how actual changes in the distribution of the population might have affected violence, holding transport costs constant. To demonstrate this, we apply parameter estimates from the beginning of the conflict (the 1970s) to the distribution of population in the 1980s. In this way we can predict the biggest reductions of local violence in the 1980s, and show that *changes* in the composition and distribution of population from the 1970s to the 1980s can explain large parts of the overall fall of violence in this period.

While the data we use is specific, we believe the model of violence as an interaction across space to be widely applicable. It is particularly useful for conflict settings of "complex warfare", i.e. civil conflicts that blur the traditional distinction between insurgency and sectarian violence. Recent conflicts in Syria, Ukraine, Yemen, Mali, Iraq and Afghanistan, for example, share elements with traditional guerrilla warfare, but also feature a large amount of violence between different religious or ethnic groups.[5] A series of estimates of violence decay could also be used to forecast the violence potential of countries and regions that are currently peaceful.

A caveat applies to our argument. We study how geographical proximity affects the risk of attacks in an ongoing conflict. This focus makes perfect sense in the short-run when fighting is acute. However, in the long-run, positive interactions between ethnic or religious groups could build trust between them and the actual motives for attacks may be reduced (see Rohner, Thoenig and Zilibotti, 2013). Hence, while bigger geographical distances can indeed reduce the number of attacks during a conflict (as emphasized by the current paper), in post-conflict reconstruction "building bridges" and reducing inter-group distance may be important policies to re-enforce peace. This subtle point has important policy implications: While physically separating groups (e.g. through so-called "peace lines" in Northern Ireland) may indeed be justifiable while fighting is still virulent, it may be optimal to tear down such walls once conflict is over and reconciliation starts.

The paper is organized as follows: Section 2 links our framework to existing concepts and surveys the related literature, while in Section 3 we set up a simple formal model of spatial interaction, predicting the origin and destination of attacks. In Section 4 we discuss the context of the "Troubles" in Northern Ireland, and present the data, whereas in Section 5 we carry out

[5] Support by the population plays a key role even in asymmetric civil conflicts like insurgencies. See, for example, US Army (2006).

the econometric analysis and present the main results and robustness checks. In Section 6 we show how the model can be usefully applied to generate novel insights. Section 7 provides a discussion of external validity and Section 8 concludes. Four appendices provide further details and results.

2 Links to Existing Concepts and Related Literature

Conceptually, our approach aims to build a bridge between the cross-country conflict literature and research using micro data. We want to do this by introducing the idea of transport costs into a canonical model of conflict.[6] In this section we first motivate this research agenda from an empirical perspective and then discuss related literature.

When cross-country studies link ethnic / religious diversity to conflict, their focus lies on the role of the overall size of different ethnic groups (i.e. *ethnic polarization or fractionalization* measures). This corresponds to making the implicit assumption that – for given fixed group population proportions– the average distance between members of the groups does not matter. Figure 2 illustrates the shortcomings of this assumption. Both the country of the left panel and the country of the right panel have the same number of regions (12) and the same level of nationwide population shares (with ethnic groups A and B being present in 6 regions each in both countries). However, in the left panel the average distance of a given region populated by A to the closest region populated by B is far greater than in the right panel where each of the six A regions is directly bordering some of the six B regions. When one assumes that the cost of committing attacks is increasing in the distance from the target, then the country in the right panel faces a higher expected number of attacks, despite the fact that it has the same population shares as the country to the left. Hence, our model can help to understand country heterogeneity in violence holding composition constant.

[6] This approach has been extremely successful in the trade literature with recent contributions by Donaldson (2018) and Fajgelbaum and Schaal (2017) integrating trade models with empirical measures of trade costs to shed light on the distribution of economic activity across space.

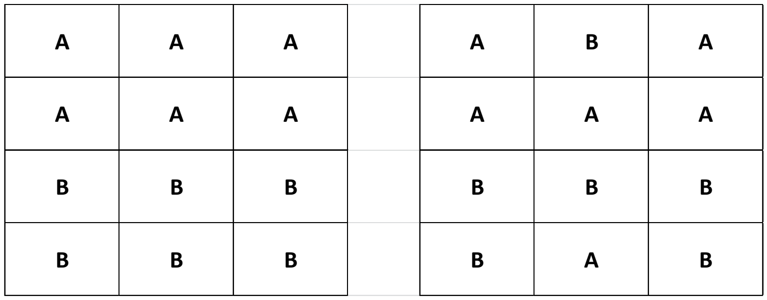


Figure 2: Two countries with the same ethnic composition but different spatial interaction

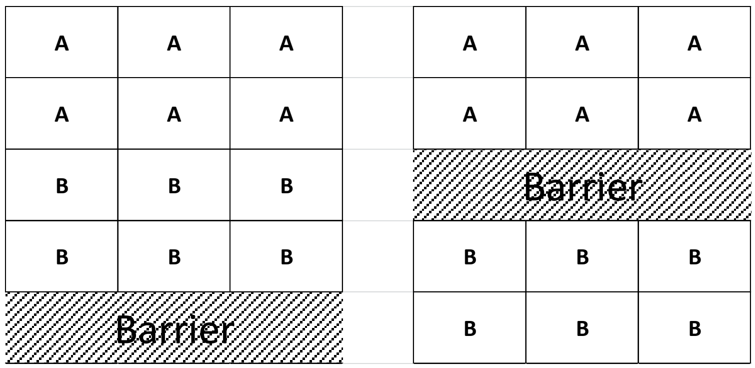


Figure 3: Same level of segregation but different spatial interaction

In addition, a model based on interactions can also take into account features like terrain characteristics that affect the way that these interactions play out. In Figure 3 we depict an extreme case. While in the left panel the "barrier" (which can be natural, e.g. a mountain, or artificial, e.g. a separating wall) is at the country borders, in the right panel it is in the middle between the two groups. Hence, even for a similar degree of *segregation*, the level of spatial interaction can be very different depending on the topology of the interaction (e.g. the location of barriers). Note that the logic is similar if for example instead of the existance of a barrier the population density varies across different regions. Conflict incentives would be smaller if low population density zones are located where the groups are close (i.e. in the second and/or third row of the left panel of Figure 2) than when they are located at places far away from other groups (i.e. in the first and/or fourth row of the left panel of Figure 2). Again, even for a similar degree of *segregation*, different locations of low and high population density areas can result in very different patterns of spatial interaction.

Figure 4 illustrates the idea behind our identification strategy. The figure shows a spatial

A	A	A
A Violence	A Violence	A Violence
B	B	B
B	B	B

A Violence	A Violence	A Violence
A	A	A
B	B	B
B	B	B

Figure 4: Different violence patterns for the same group constellation

distribution of ethnic groups A and B and two violence distributions. Violence, indicated by a grey shading, in the example on the left, is concentrated at the boundary between group A and B, while this is not the case in the right panel.

Note, that the standard method of regressing violence on characteristics within units would not indicate any difference between these two patterns. Both examples will register a correlation of violence with characteristic A. Yet, violence in the left panel could also be generated by attacks of B on A. Hence, ignoring the interaction between groups across space may result in misinterpretation and erroneous conclusions. Note also that running an existing standard *spatial econometrics* regression, such as a Spatial Durbin model (SDM), would not help if violence is indeed driven by the *interaction* of A and B.

In terms of particular contributions, our paper is related to the theoretical literature on ethnic and religious conflict (e.g. Horowitz, 2000; Varshney, 2001; Esteban and Ray, 2008, 2011; Rohner, 2011; Caselli and Coleman, 2013), and the empirical studies linking ethnic diversity to civil war at the country-year level (see. Fearon and Laitin, 2003; Collier and Hoeffler, 2004; Montalvo and Reynal-Querol, 2005; Cederman and Girardin, 2007; Collier and Rohner, 2008; Collier, Hoeffler, and Rohner, 2009; Esteban, Mayoral and Ray, 2012; Michalopoulos and Papaioannou, 2016). These papers generally find that ethnic heterogeneity (and in particular ethnic polarization) increases the risk of conflict, but – contrary to our current contribution – they do not study the spatial patterns of ethnic violence.[7] In a different vein, the impact of segregation is still

[7] Results in Spolaore and Wacziarg (2016) suggest hat this might not hold for international wars where genetically

controversial, with some scholars finding that it increases the risk of ethnic conflict (Diez Medrano, 1994; Olzak et al., 1996), while others argue that "partition", could be a solution to ethnic conflict (Horowitz, 2000).[8]

In recent years there has been an increasing number of papers studying violence at a disaggregate, local level (e.g. La Ferrara and Harari, 2012; Rohner, Thoenig, and Zilibotti, 2013b; Dube and Vargas, 2013; Berman et al., 2017; König et al., 2017), but most of these contributions do either not contain a formal model of conflict or do not take into account the local ethnic composition, usually due to data limitations.[9] Also the micro-level literature on insurgency and counter-insurgency is relevant, see Kalyvas (2006), Lyall (2010), Bhavnani et al (2011), Kocher, Pepinsky and Kalyvas (2011), and Berman, Shapiro and Felter (2011).

Maybe closest to our contribution is the literature focusing on spatial patterns of violence. There is a small literature in political science studying –inspired by the epidemiological literature on the spread of diseases– diffusion and clustering patterns of violence over space and time (Townsley, Johnson, and Ratcliffe, 2008, Schutte and Weidmann, 2011). Further, Novta (2016) builds a simulation-based model of how conflict spreads. Contrary to our setting of insurgency and terrorism, her framework is designed to study traditional military warfare between two standing armies. The features of her model are found to be consistent with the spread of violence in the 109 municipalities of Bosnia. Novta models the armed groups in each municipality as separate players who can only attack in their home village while the focus of our framework lies precisely on the across-ward attacks.[10] Bhavnani et al. (2014) link segregation to urban conflict, using a simulated agent-based model, calibrated for Jerusalem. Finally, the purely empirical

similar populations are engaged more in conflict.

[8]Sambanis (2000) concludes that partition does not significantly prevent conflict.

[9]There are also a few papers selecting an intermediate level of disaggregation and building a panel dataset on the ethnic group level covering a large number of countries (e.g. Buhaug, Cederman, and Rod, 2008; Morelli and Rohner, 2015; Esteban, Morelli and Rohner, 2015). However, their level of disaggregation is still much less fine-grained than in the current paper, and they do not focus on local ethnic cleavages and the interaction between ethnic groups across regions.

[10]Klasnja and Novta (2016) apply a related framework to Hindu-Muslim riots and the Bosnian Civil War.

contribution of Balcells, Daniels, and Escribà-Folch (2016) studies post-conflict sectarian clashes in Northern Ireland from 2005-2012. In a nutshell, a main difference between our current paper and the existing work on spatial violence patterns is that –contrary to the existing literature– our empirical analysis estimates the structural parameters of a formal model of optimizing, farsighted players.

Finally, the predictive power of our framework is also useful when it comes to forecasting the impact of conflict on economic outcomes. Besley and Mueller (2012) show for Northern Ireland that compared to peaceful areas, housing in the most violent areas sold for between 2 and 17 percent less - depending on the level of violence, and Mueller (2016) shows that changes in the distribution of violence within a country can have a substantial impact on aggregate growth. Thus, predicting well the location of attacks does not only help in forecasting local economic outcomes, but also countrywide performance.

3 Model

In this section we provide a game-theoretic model of local violence, where two groups are in a contest about appropriating rents. In line with the conflict economics literature, the share of rents grabbed by a group depends on its relative fighting effort. In our setting, the two groups locally recruit fighters for attacking a weighted average of opponents nearby. It turns out that this simple framework will allow us to predict the spatial distribution of violence in Northern Ireland to a stunning degree.

3.1 Set Up

In this one-period framework we model violence in a country with n regions indexed by i. In each region live two groups labelled, to fix ideas, $g \in \{c, p\}$. The population of group g in region (ward) i is N_i^g, where $i \in \{1, ..., n\}$, and their distribution across regions can be expressed by

$$\mathbf{N}^g = \begin{pmatrix} N_1^g \\ \vdots \\ N_n^g \end{pmatrix}.$$

Violence in these regions is conducted by two paramilitary groups that recruit themselves from the groups g, denoted F_i^g, forming

$$\mathbf{F}^g = \begin{pmatrix} F_1^g \\ \vdots \\ F_n^g \end{pmatrix}.$$

The central leaderships of each of the two paramilitary groups want to maximize the share of rents R that they capture. These rents can be thought of as nationwide gains of holding power, which we assume to be private goods.

For the purpose of rent-maximization both group leaderships have to decide simultaneously on recruiting the optimal number of local fighters in each region.

The share of rents captured by a group g is given by the following Tullock-form contest-success-function,

$$\frac{A^g}{A^g + A^{-g}},$$

where A^g are total attacks inflicted by group g, A^{-g} are attacks inflicted by group $-g$. Note, that, in order to make the model solvable, we distinguish attacks from casualties which are a random outcome. In other words, we assume that the competition for rents is affected by how many attacks the group makes and not how deadly they are.

Recruiting fighters is costly. Typically, salary costs of fighters should be thought of as convex, as the first few hirings will be cheap given that it will be feasible to target exclusively individuals with low wages in the regular economy (and hence low opportunity costs of fighting) and/or with low moral costs of killing. When extending the pool of fighters in a region, the group also needs to recruit individuals with better outside options and higher moral costs who will require higher monetary compensation.

Further, the larger the population of locals of a given group in a given region the cheaper the hiring costs, as the fighters face lower risks of identification and being arrested and can benefit from more local support and safehouses.

We assume the following functional form of a convex cost function which captures these aspects:

$$\frac{1}{2}\frac{(F_i^g)^2}{(N_i^g)^\mu},$$

where $\mu \geq 0$.

This functional form has several advantages. First of all, using a square term of the effort variable (and normalizing by 1/2) is the simplest way of capturing convexity, and has been used in a large number of contributions in different fields of economics. Second, the term $(N_i^g)^\mu$ is very flexible: If $\mu = 1$, then the costs of recruiting for group g drop with higher population from group g; if $\mu = 0$, local support doesn't matter in the sense that the costs of recruiters scales only with the total number of fighters in the region. We find that $\mu \approx 1$ yields the best fit to the data which indicates that local support for the fighting effort is important.

The number of attacks is a function of the available targets and their proximity. We model interaction across space flexibly by defining a group-specific symmetric spatial weights matrix

$$\mathbf{W}^g = \begin{pmatrix} \mathbf{W}_1^g & \cdots & \mathbf{W}_n^g \end{pmatrix} = \begin{pmatrix} w_{11}^g & \cdots & w_{1n}^g \\ \vdots & \ddots & \vdots \\ w_{n1}^g & \cdots & w_{nn}^g \end{pmatrix}$$

with $w_{ij}^g = w_{ji}^g$ for all i, j. The spatial weight w_{ij}^g parametrizes how costly it is for group g to project violence from region i to region j. The number of attacks perpetrated by group g emanating from location i are given by

$$A_i^g = F_i^g \sum_{j=1}^{n} w_{ij} N_j^{-g} = F_i^g \left(\mathbf{W}_i^g\right)' \mathbf{N}^{-g}, \tag{1}$$

where $-g$ denotes the opposite group. This means that attacks launched from i by g are the interaction of the number of perpetrators (fighters) in i and the spatially weighted number of potential victims (population) in all regions. Thus, overall attacks by group g are

$$A^g = \sum_{i=1}^{n} A_i^g = \left(\mathbf{F}^g\right)' \left(\mathbf{W}^g\right) \mathbf{N}^{-g}.$$

Putting these elements together, the payoff function of a group g's leadership becomes

$$\pi^g = \frac{A^g}{A^g + A^{-g}} R - \frac{1}{2} \sum_{i=1}^{n} \left(\frac{(F_i^g)^2}{(N_i^g)^\mu} \right).$$

3.2 Characterization of the Equilibrium

The equilibrium is determined by the number of fighters that each group recruits in each region. Each group has to optimally select recruiting numbers for every region, F_i^g, given the number of fighters that the other group recruits. Hence, we will obtain a system of $2 \times n$ first-order conditions (FOC) and $2 \times n$ unknowns. Given that in each FOC the benefits of a marginal recruit (i.e. the first term) are strictly concave, while the marginal costs (i.e. the second term) are strictly convex, the second-order conditions (SOC) hold and there is a unique interior equilibrium.

The marginal fighting strength increase of an additional fighter of group g in region i corresponds to

$$\frac{\partial A^g}{\partial F_i^g} = (\mathbf{W}_i^g)' \, \mathbf{N}^{-g},$$

which implies that the incentive to recruit fighters locally will be a weighted function of the possible targets for those fighters. For each region i we therefore get a FOC, which for group g is given by

$$\frac{\partial \pi^g}{\partial F_i^g} = \frac{(\mathbf{W}_i^g)' \, \mathbf{N}^{-g} \tilde{A}^{-g}}{\left(\tilde{A}^g + \tilde{A}^{-g}\right)^2} R - \frac{\tilde{F}_i^g}{(N_i^g)^\mu} = 0,$$

where $\tilde{A}^g$, $\tilde{A}^{-g}$ and $\tilde{F}_i^g$ are equilibrium values. The optimal choice of local fighting effort satisfies

$$\tilde{F}_i^g = \frac{\tilde{A}^{-g}}{\left(\tilde{A}^g + \tilde{A}^{-g}\right)^2} R \times (\mathbf{W}_i^g)' \, \mathbf{N}^{-g} (N_i^g)^\mu. \tag{2}$$

Equation (2) says that local fighting effort is a function of a part which is constant across all regions, $\frac{\tilde{A}^{-g}}{\left(\tilde{A}^g + \tilde{A}^{-g}\right)^2} R$, and a part which varies from region to region $(\mathbf{W}_i^g)' \, \mathbf{N}^{-g} (N_i^g)^\mu$. Note, that $(\mathbf{W}_i^g)' \, \mathbf{N}^{-g} (N_i^g)^\mu$ is the weighted sum of all population in group $-g$ interacted with $(N_i^g)^\mu$. The easier it is to recruit, i.e. the higher $(N_i^g)^\mu$, the more fighters will be recruited locally. Further, the more targets are in reach, i.e. the higher $(\mathbf{W}_i^g)' \, \mathbf{N}^{-g}$, the more fighters will be recruited.

In the empirical analysis we will be able to make use of the fact that the relative fighting effort between regions is only a function of demographic exogenous variables and the effectiveness of fighting captured by the spatial weights w_{ij}^g. While the absolute magnitude of the w_{ij}^g parameters is difficult to interpret, one should expect all $w_{ij}^g \geq 0$, and $w_{i'j}^g < w_{ij}^g$ if $\text{dist}(i\prime, j) > \text{dist}(i, j)$, and $w_{ij'}^g < w_{ij}^g$ if $\text{dist}(i, j\prime) > \text{dist}(i, j)$. In other words, we expect effectiveness to decrease in distance.

Given the equilibrium number of fighters originating from each region it is easy to calculate the number of attacks targeted at each region. Casualties of group g in region i are given by

$$cas_i^g = N_i^g \left(\mathbf{W}_i^{-g}\right)' \tilde{\mathbf{F}}^{-g} + \varepsilon_i, \tag{3}$$

where $\tilde{\mathbf{F}}^{-g}$ is the vector version of equation (2) given by

$$\tilde{\mathbf{F}}^{-g} = \frac{\tilde{A}^g}{\left(\tilde{A}^g + \tilde{A}^{-g}\right)^2} R \times diag\left[\left(\mathbf{W}^{-g}\right)' \mathbf{N}^g\right] (\mathbf{N}^{-g})^{\mu}, \tag{4}$$

where $(\mathbf{N}^{-g})^{\mu}$ is an element-by-element exponent and $diag\left[\left(\mathbf{W}^{-g}\right)' \mathbf{N}^g\right]$ is a matrix with the values of $\left(\mathbf{W}^{-g}\right)' \mathbf{N}^g$ on the diagonal and zero otherwise.[11] The error term ε_i, with $E(\varepsilon_i) = 0$, in equation (3) reflects the fact that there is some randomness in the transmission from attacks to casualties. Not all successfully carried out attacks do result in the same number of fatalities, which is the variable observed by the econometrician.

Equation (3) captures the essence of our theory. Violence at location i is the result of an interaction between targets in location i, N_i^g, and the number of attackers based in all locations, $\tilde{\mathbf{F}}^{-g}$. How dangerous these interactions are for the population at i depends on the vector of weights $\mathbf{W}_i^{-g}$. Note, however, that the full weighting matrix for all locations, $\mathbf{W}^{-g}$, also plays a role (through $\tilde{\mathbf{F}}^{-g}$) because it determines how many fighters are recruited by the other group.

Thus, a general fall in transport costs (increase in w_{ij}^{-g}) has two effects. First, fighters in the neighborhood of i are more effective and therefore attack more in region i. This is the effect coming from $\mathbf{W}_i^{-g}$ in equation (3). Second, more fighters are recruited in all other locations because they can attack more effectively in their respective neighborhoods. This effect is captured by the matrix $\mathbf{W}^{-g}$ in equation (4).

[11] We have $\tilde{\mathbf{F}}^{-g} = \frac{\tilde{A}^g}{\left(\tilde{A}^g + \tilde{A}^{-g}\right)^2} R \times \begin{pmatrix} N_1^g w_{11}^{-g} + N_2^g w_{21}^{-g} ... + N_n^g w_{n1}^{-g} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & N_1^g w_{1n}^{-g} + N_2^g w_{2n}^{-g} ... + N_n^g w_{nn}^{-g} \end{pmatrix} \begin{pmatrix} \left(N_1^{-g}\right)^{\mu} \\ \vdots \\ \left(N_n^{-g}\right)^{\mu} \end{pmatrix}$.

4 Empirical Implementation: The Data

The structural parameters of the model are estimated using data from the conflict in Northern Ireland. This is one of the most important and costliest conflicts in a developed country over the last decades. Studying the Northern Irish "Troubles" allows us to draw on very fine grained group location and fighting event location data. Below we shall start by describing the context of this conflict, before providing a detailed description of the data used.

4.1 Context of Conflict in Northern Ireland

The Northern part of Ireland, Ulster, has been religiously divided since its conquest by England and the Reformation, taking both place in the 16th century.[12] Since then the Catholic population from Gaelic Irish origin and the Protestant population of English and Scottish settlers have lived "separate lives" characterized by very stable patterns of land holdings and relatively few religiously mixed marriages (Mulholland, 2002). When the Republic of Ireland achieved independence from Britain in 1922, the six Northern counties of Ireland remained part of the UK.

In the early 1920s "Troubles" broke out with the Irish Republican Army (IRA) challenging British authority over Ulster and engaging in violent combats against the British troops and Protestant paramilitary organizations such as the Ulster Volunteer Force (UVF). The following decades were characterized by "home rule" and the new Parliament of Northern Ireland at Stormont near Belfast. The political divide persisted between the Catholic Nationalists (also called Republicans) who wanted to join the Republic of Ireland and the Protestant Unionists (also called Loyalists) who wanted to remain united with the UK.

While in the 1950s and early 1960s there were relatively low levels of political violence, in 1968 the situation became again more confrontational when the Civil Rights Movements asked for more rights for Catholic citizens. Some of the initially peaceful demonstrations and marches

[12] This subsection draws heavily on Mulholland (2002).

were met with repression and resulted in fatalities. From August 1969 onwards sectarian violence exploded. In September 1969 radical militants took control of the previously dormant IRA and created its radical wing, the Provisional IRA. The "Provos" achieved an ever tighter grip over traditional Catholic working class strongholds like the Falls Road in Belfast or the Bogside in Derry.

Further, alarmed by the rise of the IRA and the seeming willingness of the UK government to make political concessions, loyalist paramilitary organizations stepped up in the 1970s, intimidating Catholic families from mixed and Protestant areas and starting a violent campaign against civilian Catholics.

After 1976 the UK built up a stronger Royal Ulster Constabulary (RUC) that together with the British Army and the SAS troops stepped up efforts to militarily weaken the IRA. This effort led the loyalist paramilitaries to lower their violence and the IRA to retrieve from large-scale open confrontations and to adopt a cellular structure common in terrorist organizations.

Even carefully planned attacks by the paramilitary groups had to rely on operational centres based on religion. Dillon (1999), for example, describes an IRA operation in October 1972 as follows:

"The intelligence officer of the 1st Battalion said Twinbrook was the best for an assault on the laundry van [...]. He reckoned that if the van was attacked in Twinbrook an IRA unit could make an escape with ease and be in the safety of the Andersontown district within a matter of five to ten minutes."(Dillon 1999, page 42).

In Andersontown the 1971 census counted 5588 Catholics and 51 Protestants. The quote shows that the IRA was operating from and around this Catholic ward. This made attacks on Protestants and state forces close to Andersontown more likely.

4.2 Data from Northern Ireland

We use two main data sources. Data on religious composition is from the UK 1971 census and is provided by NISRA (2015). Most data on violence comes from Sutton (1994) and has been updated by the Conflict Archive on the Internet (CAIN) website (CAIN, 2015). We use address data in the description of killings to derive geo-references data. We then use these references to match killings to wards and grid-cells. The violence data is unique as it reports the religion of each victim (unless for members of the state forces) and the group that attacked him or her.

We have data on 582 wards (our unit of analysis), which are regrouped into 101 larger District Electoral Areas (DEA) which again map into 26 local government districts.[13] Table 1 shows the summary statistics of the most relevant variables. The number of Catholics and Protestants are in thousands. Table 1 also summarizes our data on conflict-related casualties. The special feature of this data is that it reports the group affiliation of victims of violence.

We first notice that while the average number of casualties per ward is relatively small, the variance is very large. While in many wards no fatalities occur, the most violent ward records 97 casualties. We further see that casualties are relatively evenly split between catholic and protestant victims and that there is a large heterogeneity in the group composition of wards and their neighborhood.

In our main analysis we focus on the settlement patterns and violence data from the 1970s, when most of the violence takes place. Table 1 shows that there are 3.14 casualties on average per ward in the 1970s and 1.25 casualties in the 1980s. In a sensitivity test, we also show robustness of the findings when including the 1980s. We focus on the first decade (1970s) to ensure that reverse causality between settlement patterns and violence are less of a concern. Since the census data is from the start of the respective decade we should be able to capture the effect of settlement patterns before violence broke out. It is much harder to argue this for the 1980s or 1990s. For this reason we focus on a cross-section of wards for the 1970s (the potential endogeneity of the 1980s and 1990s census population data prevents us from making use of the panel structure over the three decades).

Figure 5 below illustrates the type of data we use, focusing on a part of Belfast for a particu-

[13]The wards are from the District Electoral Areas (Northern Ireland) Order 1993. These boundaries have been revised in 2014. A list of 1993 wards and their corresponding DEAs can be found under http://www.legislation.gov.uk/uksi/1993/226/made.

Data from the 1970s	Observations	Mean	SD	Min	Max
casualties	582	3.14	8.63	0	97
catholic casualties	582	1.45	4.71	0	62
protestant casualties	582	1.69	4.46	0	46
catholics (in 1000s)	582	1.18	1.08	0	9.72
protestants (in 1000s)	582	1.45	1.88	0	14.42
catholics in direct neighbourhood (in 1000s)	582	7.08	4.91	0.36	32.84
protestants in direct neighbourhood (in 1000s)	582	8.07	10.37	0.00	76.97
catholics in two wards distance (in 1000s)	582	16.45	9.46	0.92	51.25
protestants in two wards distance (in 1000s)	582	18.32	21.77	0.21	138.51

Data from the 1980s	Observations	Mean	SD	Min	Max
casualties	582	1.25	2.54	0	19
catholic casualties	582	0.48	1.36	0	11
protestant casualties	582	0.77	1.61	0	13
catholics (in 1000s)	582	1.44	0.84	0.04	5
protestants (in 1000s)	582	1.07	1.33	0.00	7
catholics in direct neighbourhood (in 1000s)	582	8.61	4.40	1.04	23
protestants in direct neighbourhood (in 1000s)	582	5.82	7.24	0.00	45
catholics in two wards distance (in 1000s)	582	19.74	9.78	1.86	58
protestants in two wards distance (in 1000s)	582	13.09	15.61	0.00	97

Notes: From CAIN (2015), Sutton (1994) and NISRA (2015). We code casualties of the state forces as protestant casualties if a ward has casualties whose religion is not revealed.

Table 1: Summary Statistics

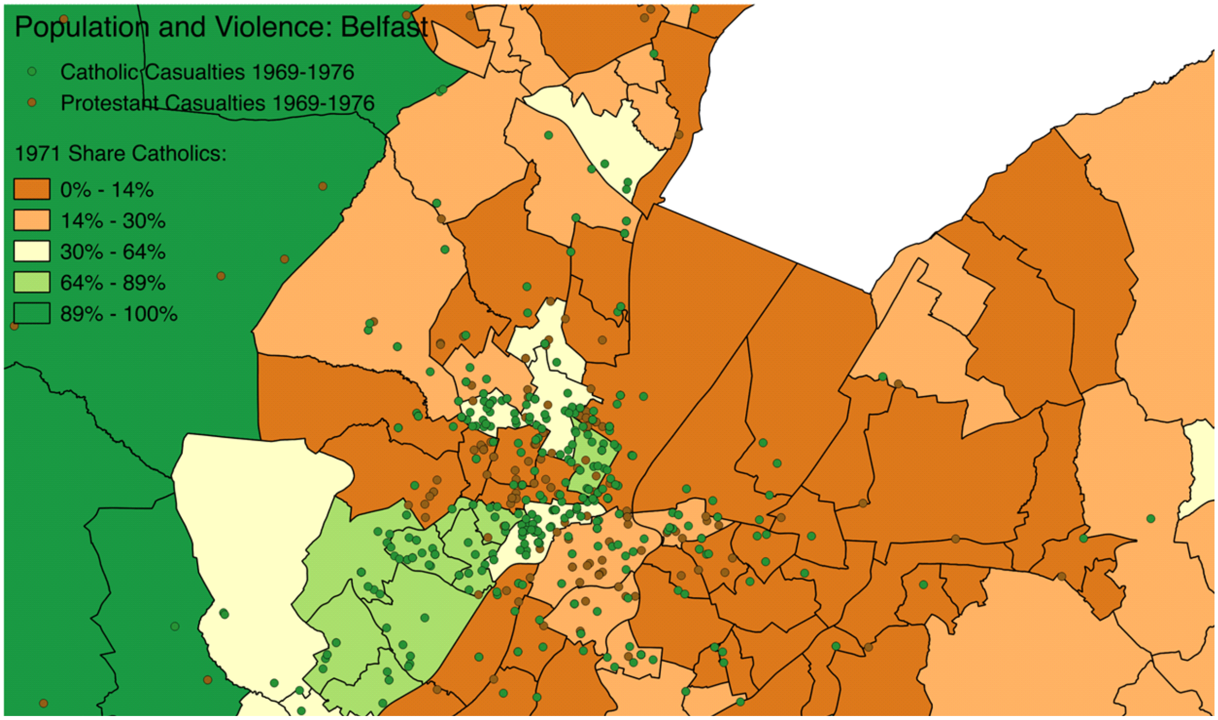


Figure 5: Map of inner Belfast wards with information on demographics and fatalities

larly violent period of the conflict (1969-1976). Our data contain information on the demographic composition of all administrative wards (with the white area in the upper-right corner depicting the sea), as well as information on the location and religious affiliation of all recorded fatalities. In line with our theory we see that many fatalities take place in either religiously mixed wards or in religiously homogeneous wards located close to strongholds of the other religious community. In contrast, religiously homogenous wards located far away from the other religious group experience only small levels of violence.

5 Estimations

One unique feature of our setting and data is that it allows us to estimate the decay of distance parameters captured by the spatial weights matrix $\mathbf{W}^g$. In this section we first estimate $\mathbf{W}^g$ and then demonstrate the dramatic gains the estimated model brings towards understanding the distribution of violence.

5.1 Estimation of the Decay of Distance Parameters

Applying the model (see equation (3)) to Northern Ireland, we now label the Protestants (p) and Catholics (c) killed in some region (ward) j as cas_j^p and cas_j^c, respectively. The data on Northern Ireland do not allow R to be identified, so we normalize it to 1. We also normalize the parameter μ to 1 (but show in the Appendix B that a maximum likelihood grid search indeed suggests μ to be around 1, and that the results are robust to other values of μ). Again, for the sake of tractability, we shall first focus on within ward violence and on violence between neighbors of the first degree. In a second step, we will also consider violence between higher degree neighbors.

For the empirical estimation, we shall assume that the spatial weight for within-ward interactions is the same in all wards, i.e. $w_{ii}^g = w_{jj}^g$. Similarly, the spatial weight for direct neighboring wards is assumed to be the same for all neighbor pairs, i.e. if i, j, l are a triad of neighboring wards, then $w_{ij}^g = w_{il}^g = w_{jl}^g$. For simplicity, we label these coefficients of interest of the spatial weights matrix $\mathbf{W}^g$ as k_0^g, $g = \{c, p\}$, for within-ward violence (i.e. where w_{ij}^g has $i = j$), and as k_1^g for direct neighboring wards (i.e. with w_{ij}^g where i and j are direct neighboring wards).

With these assumptions we can simplify equation (3). Call $n1(j)$ the neighboring wards of j. We can then write casualties suffered by groups p or c in ward j as a function of targets, N_j^g, interacted with the number of attackers $\tilde{F}_j^{-g}$ and $\tilde{F}_{i\in n1(j)}^{-g}$, i.e. we can write

$$\begin{aligned} cas_j^p &= N_j^p \left(\mathbf{W}_j^c\right)' \tilde{\mathbf{F}}^c + \varepsilon_j & (5) \\ &= N_j^p \left(k_0^c \tilde{F}_j^c + k_1^c \sum_{i\in n1(j)} \tilde{F}_i^c \right) + \varepsilon_j, \\ cas_j^c &= N_j^c \left(k_0^p \tilde{F}_j^p + k_1^p \sum_{i\in n1(j)} \tilde{F}_i^p \right) + \varepsilon_j, & (6) \end{aligned}$$

where the equilibrium number of attackers in each location is given by

$$\begin{aligned} \tilde{F}_j^c &= \frac{\tilde{A}^p}{\left(\tilde{A}^c + \tilde{A}^p\right)^2} [(k_0^c N_j^p + k_1^c \sum_{i\in n1(j)} N_{n1(i)}^p)(N_j^c)^\mu], & (7) \\ \tilde{F}_j^p &= \frac{\tilde{A}^c}{\left(\tilde{A}^c + \tilde{A}^p\right)^2} [(k_0^p N_j^c + k_1^p \sum_{i\in n1(j)} N_{n1(i)}^c)(N_j^p)^\mu]. & (8) \end{aligned}$$

Note, that equations (7) and (8) indicate that the recruitment of attackers is driven by the respective neighborhood. This implies that, in order to estimate equations (5) and (6), we need

VARIABLES	(1) protestant casualties	(2) protestant casualties	(3) catholic casualties	(4) catholic casualties
k0	10.88***	9.98***	10.48***	9.68**
	(0.93)	(1.43)	(2.79)	(4.51)
k1	1.77***	1.20***	2.94***	1.63
	(0.11)	(0.40)	(0.38)	(2.44)
k2		0.41		0.91
		(0.35)		(0.94)
p value: k0=k1	0.00	0.00	0.02	0.23
p value: k0=k2	.	0.00	.	0.02
p value: k1=k2	.	0.29	.	0.83
Observations	582	582	582	582
R-squared	0.61	0.61	0.76	0.77

Notes: Robust standard errors in parentheses. Standard errors are clustered at the electoral district level (101 clusters). *** p<0.01, ** p<0.05, * p<0.1. "Protestant casualties" are casualties of state forces and protestants. "Catholic casualties" are casualties of catholics. The model's parameter "mu" (determining how the recruitment of fighters relies on local population) is normalized to 1. "k0-k2" are decay parameters. k0 captures the transport cost of conducting attacks within the same ward. k1 captures the transport cost of conducting attacks in the direct (bordering) neighbourhood of the ward. k2 captures the transport cost of crossing one ward to carry out an attack. In columns (1) and (2) we report the k parameters of catholic paramilitaries and in columns (3) and (4) we report the k parameters of protestant armed groups.

Table 2: Main estimation of the spatial weight parameters, separately for protestant and catholic casualties

data for the composition of the direct neighborhood and data for the composition of the neighbor's direct neighborhood. Variation in the neighborhood composition is essential for our identification strategy.

We take the number of casualties caused by the two groups as the best estimate for the number of equilibrium attacks, $\tilde{A}^p$ and $\tilde{A}^c$, and assume that all protestant victims and casualties amongst the state forces were caused by catholic fighters and that all catholic victims were caused by protestant fighters. This brings $\tilde{A}^c + \tilde{A}^p$ as close as possible to the total number of casualties while still using information on the violence perpetuated by the two sides in the conflict.

Table 2 displays the results of our estimates of the spatial weight parameters in our model. The parameter k_0^g captures the effectiveness of attacks within the same ward, k_1^g captures the effectiveness of attacks in the direct (bordering) neighborhood of the ward, and k_2^g captures the effectiveness of attacks of second-degree neighbors. We estimate the expressions for cas_j^p, and cas_j^c, from equations (5) and (6), respectively, running a non-linear regression (see Davidson and MacKinnon, 1993) and let the estimator pick the values of k_0^g, k_1^g, and k_2^g that maximize the fit.[14] Focussing in column (1) on violence against Protestants and on k_0^c and k_1^c only, we find that all k-coefficients are precisely estimated (both significant at the 1 percent level) and that k_0^c is substantially larger than k_1^c, showing a clear decay. In line with our hypotheses, there is indeed a cost of projecting violence over distance, and the attacks decay across ward borders. According to the estimates of column (1), the violence potential originating from a given ward is about six times smaller when the ward border needs to be crossed than within-ward.

In column (2), also second degree neighboring wards are included in the analysis (k_2^c). Again, the k-coefficient gradually decreases when crossing an additional ward border, displaying a clear-cut ranking of $k_2^c < k_1^c < k_0^c$. Columns (3)-(4) display similar estimations for catholic casualties. The coefficients of k_0^p and k_1^p are somewhat comparable to the ones found for protestant fatalities in columns (1)-(2), and the ratio of k_1^g/k_0^g is of a similar magnitude (i.e. roughly four) as in columns (1)-(2) (i.e. roughly six). In column (4) we again include second degree neighboring wards. While the qualitative picture of column (4) is very similar to column (2), the coefficients are less precisely estimated.

It is important to stress that the similarity of results in columns (1) and (3) are not a given. Many wards had large catholic or protestant majorities so that population composition varied dramatically between Protestants and Catholics in 1971. This means that the variation used to identify the parameters k_0^c and k_1^c is quite different to the variation used to identify k_0^p and k_1^p.

As mentioned above, in Table 2 we have normalized the model's parameter μ (that determines how the recruitment of fighters relies on local population) to 1. Given that it seems difficult to find a reliable proxy for μ, this is a reasonable way of proceeding. We include two additional robustness tables, relaxing this normalization. First, we perform a maximum likelihood grid search, yielding the value of μ that maximizes the overall fit of the model. The results are

[14] We use non-linear-least squares to fit the equation. We have also estimated parameters with maximum likelihood under the assumption of a negative binomial (overdispersion is a clear problem in the data). Results are qualitatively similar with precisely estimated k_0, k_1 and $k_0 > k_1$ but point estimates are lower and the model fit is worse.

displayed in Table 9 in Appendix B, which replicates Table 2, but using the μ found in the grid search. First of all, note that in all four columns the μ found is always in the neighborhood of 1, ranging from 0.78 to 1.18. Second, the estimated coefficients of k_0^g, k_1^g, and k_2^g are similar in terms of size to the ones found in the baseline Table 2.

Further, we also replicate the key results of Table 2 for different values of μ around 1. In particular, in Table 3 we show that our results for the direct neighborhood go through for $\mu = 0.5, \mu = 0.75, \mu = 1.25$ and $\mu = 1.5$. Panel A reports the results for protestant casualties and Panel B reports the results for Catholic casualties. The relative size of the coefficients changes but $k_1^g < k_0^g$ is always maintained. The estimated parameters fall for larger values of μ. This can be explained by the fact that higher values of μ imply more fighters per population. If the number of fighters increases, effectiveness of these fighters needs to decrease in order to maintain the level of violence. Also, estimates for k_0^g fall relative to k_1^g for larger values of μ. This change is driven by large mixed wards which generate a lot more within-ward violence for large μ due to the non-linearity in the recruitment technology. Note that we find that catholic casualties are best described (highest R^2) by a slightly lower μ (close to 0.75 as opposed to close to 1.25 for protestant casualties). This could be explained by the fact that protestant fighters include state forces which we expect to move more freely and therefore are less bound by local support by Protestants.

Our framework also allows us to estimate the total combined death toll of Protestants and Catholics, $cas_j \equiv cas_j^p + cas_j^c$, relying again on the structural equations (5) and (6). This is what we do in Table 4. In particular, we allow for different $k_m^c \neq k_m^p$, but assume that the relative decay of distance is similar for both population groups, i.e. $k_m^c/k_m^c = k_m^p/k_m^p$, for $m = 1, 2...M$. This is reasonable in the light of Table 2 that indeed found for both population groups similar spatial weight ratios of k_0/k_1, and k_1/k_2. It implies that we can replace the ratio k_m^c/k_m^p by a constant for all m. Call $M_c \equiv (k_m^c/k_m^p)^2$. We can then write casualties in ward j as

$$\begin{aligned} cas_j^p + cas_j^c \quad = \quad & M_c \times N_j^p \left(k_0^p \tilde{F}_j^{\prime c} + k_1^p \sum_{i \in n1(j)} \tilde{F}_i^{\prime c} \right) \\ & + N_j^c \left(k_0^p \tilde{F}_j^p + k_1^p \sum_{i \in n1(j)} \tilde{F}_i^p \right) + \epsilon_j, \end{aligned} \tag{9}$$

Panel A: protestant casualties				
	(1)	(2)	(3)	(4)
VARIABLES	mu=0.5	mu=0.75	mu=1.25	mu=1.5
k0	18.56***	13.82***	8.64***	6.71***
	(3.85)	(1.86)	(0.57)	(0.78)
k1	1.48**	1.84***	1.55***	1.31***
	(0.62)	(0.21)	(0.08)	(0.08)
Observations	582	582	582	582
R-squared	0.58	0.60	0.60	0.59
Panel B: catholic casualties				
	(1)	(2)	(3)	(4)
VARIABLES	mu=0.5	mu=0.75	mu=1.25	mu=1.5
k0	12.41*	12.13***	8.56***	6.73***
	(7.09)	(3.00)	(2.64)	(1.91)
k1	5.24***	3.89***	2.24***	1.70***
	(1.45)	(0.66)	(0.30)	(0.18)
Observations	582	582	582	582
R-squared	0.75	0.76	0.74	0.73

Notes: Robust standard errors in parentheses. Standard errors are clustered at the electoral district level (101 clusters). *** p<0.01, ** p<0.05, * p<0.1. "Protestant casualties" are casualties of state forces and protestants. "Catholic casualties" are casualties of catholics. "k0-k1" are decay parameters. k0 captures the transport cost of conducting attacks within the same ward. k1 captures the transport cost of conducting attacks in the direct (bordering) neighbourhood of the ward. Different columns display results with different assumptions on the parameter mu which captures how the cost of fighter recruitment changes with group size.

Table 3: Robustness of main specification with respect to mu

where ϵ_j is the error term of the combined regression, F_i^p is given by equation (8), and $\tilde{F}_i^{\prime c}$ corresponds to $\tilde{F}_i^c$ of equation (7) besides the fact that k_m^c is replaced by k_m^p.

This combined estimation of cas_j also allows us to compute the relative "aggressiveness of catholic paramilitaries compared to state forces and loyalist paramilitaries", captured by the parameter M_c, which intuitively tells us how many attacks are carried out by Catholics compared to Protestants for a given availability and proximity of targets. $M_c < 1$ mean that catholic paramilitaries carry out less attacks than protestant fighters for a given availability of targets, while $M_c > 1$ implies that catholic fighters are relatively more "aggressive". The interpretation of M_c of course requires caution, as any $M_c \neq 1$ could be due to various factors such as e.g. differences in motivation, organization or logistical capacity of paramilitary groups, differences in population support, advantages and constraints related to being linked to the political establishment etc. Our data do not allow us to disentangle the root causes driving the value of M_c.

Table 4 performs this joint estimation of total casualties, and shows that indeed there is a gradual decay of attack potential when crossing ward borders, with all k-coefficients being statistically significant and $k_2^p < k_1^p < k_0^p$. It is particularly re-assuring that the point estimates are very close to the estimates of k_2^p, k_1^p and k_0^p in Table 2. Further, the M_c coefficient is estimated to be around 0.6, revealing that for an identical availability and proximity of targets, assuming everything else constant, catholic paramilitaries carry out roughly 20 percent less attacks than protestant forces.[15]

A crucial aspect to keep in mind is that, while $k_0^p > k_1^p$, the latter parameter applies to a lot more interactions. The neighborhood contains a population that is more than five times larger than the population of the average ward. This implies that more than half of all attacks, according to the specification of Table 4, take place across ward boundaries.[16]

[15] We calculate this from $k_m^c/k_m^p = \sqrt{0.63} = 0.79$.

[16] For a more detailed discussion see the Appendix C.

VARIABLES	(1) all casualties	(2) all casualties
k0	8.30***	6.91**
	(1.75)	(3.01)
k1	3.45***	2.56***
	(0.26)	(0.79)
k2		0.75**
		(0.34)
Mc	0.63***	0.55***
	(0.05)	(0.13)
p value: k0=k1	0.02	0.22
p value: k0=k2	.	0.04
p value: k1=k2	.	0.08
Observations	582	582
R-squared	0.78	0.79

Notes: Robust standard errors in parentheses. Standard errors are clustered at the electoral district level (101 clusters). *** p<0.01, ** p<0.05, * p<0.1. The model's parameter "mu" (determining how the recruitment of fighters relies on local population) is normalized to 1. "k0-k2" are decay parameters. k0 captures the transport cost of conducting attacks within the same ward for state forces and loyalists (kp0 in the text). k1 captures the transport cost of conducting attacks in the direct (bordering) neighbourhood of the ward for state forces and loyalists. k2 captures the transport cost of crossing one ward to carry out an attack for state forces and loyalists. Mc captures the relative aggressiveness of republican paramilitaries compared to state forces and loyalists, (kc/kp)^2.

Table 4: Main estimation of the decay parameters, protestant and catholic casualties combined

5.2 Comparison to Alternative Models

A clear advantage of modeling the local interaction of the local population is a gain in the explanatory power of the model. In order to show this we consider two benchmarks. The first benchmark is an alternative framework where only ward population characteristics matter and where, accordingly, the violence potential is assumed to fully decay when a ward-border is crossed. Put differently, this corresponds to a setting often encountered in within-country studies in which the location of attacks and targets is not separated.

We model this alternative by regressing ward-level casualties on the numbers of Protestants and Catholics in a given ward and their interaction. In Appendix B, Table 10 depicts the regression results for this alternative specification in column (1).[17]

Figure 6 below displays a comparison of our setting (called "model") with the benchmark alternative model of full distance decay of the Appendix Table 10, column (1) (called "benchmark"). The curves represent the distribution of the residuals, i.e. $cas_j - \widehat{cas}_j$. Large numbers mean that the extent of violence is underestimated. In the benchmark model we predict violence with the population composition and interactions within the ward, whereas $\widehat{cas}_j$ in our model is given by the fitted values from equation (9). The curve capturing our model is drawn in a dashed red line, while the benchmark curve is drawn in a blue solid line. The curve of our setting is centered around zero and reaches a very high kernel density close to zero. This reveals that the fit is very good, with most wards having very similar levels of actual and fitted casualties. In contrast, the alternative model has a substantially lower fit, revealed by a larger spread away from zero (running an F-test confirms at the 1% level of significance that the alternative benchmark has a larger standard deviation of the error terms). The alternative model slightly overestimates violence in a large number of wards and grossly underestimates it in a few other wards. This is not only a result of not taking cross-border attacks into account but also of ignoring the changes

[17] In column (2) of the Appendix Table 10 we display another alternative specification which is also common in the literature. This specification ignores population size and predicts casualties with the share of catholics and its square. This specification has almost no predictive power.

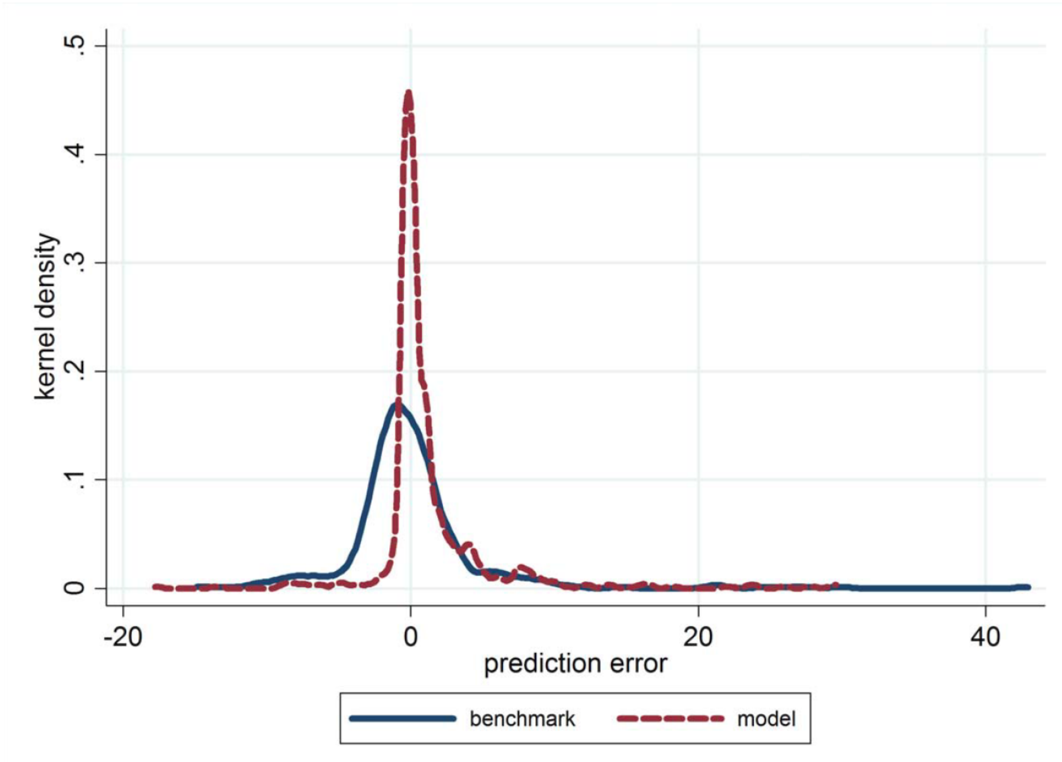


Figure 6: Our model compared to full decay

in motivation to fight in areas with a lot of potential targets.[18]

The second natural benchmark to consider is a model assuming no decay of violence potential over space. This is the implicit assumption of many country-level studies assuming that only the overall population composition but not their location matters (see Figure 2). According to this "no spatial decay" benchmark the population composition in a given ward and in its neighborhood should only affect casualties through the nationwide presence of potential victims, i.e. this boils down to setting $k_0 = k_1 = k_2... = k_n$. Attacks are then given by

$$\widehat{cas}_j^g = \frac{N_j^g}{\sum_j N_j^g} \tilde{A}^{-g}.$$

This simply means that total casualties of group g will be distributed according to where group g

[18] To see this, imagine that k_1 is set to 0. This has two effects: First, even if the recruitment of fighters was unchanged, their effectiveness would decrease. Second, the effect is anticipated and recruitment of fighters decreases. We discuss this in detail in Appendix A.

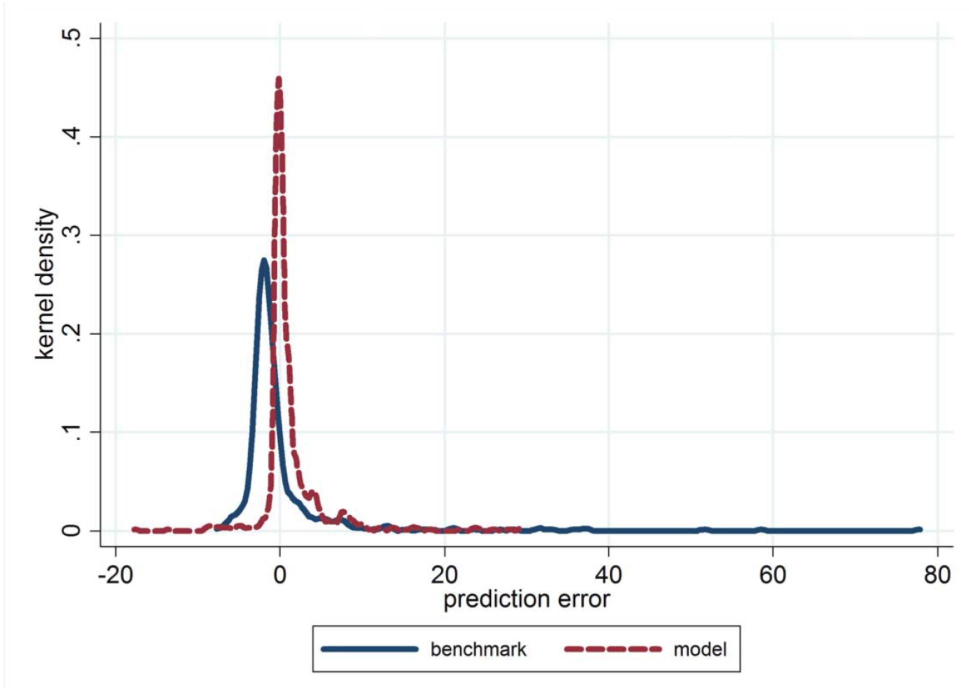


Figure 7: Our model compared to no decay

lives. From this we can calculate $\widehat{cas}_j = \widehat{cas}_j^c + \widehat{cas}_j^p$ and $cas_j - \widehat{cas}_j$. In Figure 7 we compare the fit of our setting (called "model", depicted by the red dashed curve) with this no decay benchmark (called "benchmark", displayed by the blue solid line). This reveals a substantially less good fit of the no decay benchmark, with violence in many wards being drastically underestimated (running an F-test confirms at the 1% level of significance that the alternative benchmark has a larger standard deviation of the error terms).

5.3 Robustness Checks

This subsection will be devoted to our main robustness checks on clustering and alternative location subsamples or time frames.

Table 5 shows that the statistical inference is robust to various levels of clustering standard errors. One natural alternative option for clustering would be at the parliamentary constituency or district level, although unfortunately the number of parliamentary constituencies and districts are only 18 and 26, respectively, which is below the typical lower bound of clusters required (50). Incidentally, if we ignore this issue and still cluster at these levels, as we do in columns (1) and

	(1) errors clustered at parl. constituency level	(2) errors clustered at district council level	(3) no clustering
VARIABLES	all casualties	all casualties	all casualties
k0	8.30***	8.30***	8.30***
	(1.80)	(0.55)	(3.01)
k1	3.45***	3.45***	3.45***
	(0.28)	(0.06)	(0.54)
Mc	0.63***	0.63***	0.63***
	(0.10)	(0.03)	(0.14)
Observations	582	582	582
R-squared	0.78	0.78	0.78

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Protestant casualties" are casualties of state forces and protestants. "Catholic casualties" are casualties of catholics. "mu" is normalized to 1. "k0-k2" are decay parameters. k0 captures the transport cost of conducting attacks within the same ward. k1 captures the transport cost of conducting attacks in the direct neighbourhood of the ward. k2 captures the transport cost crossing one ward to conduct an attack. Mc captures the relative aggressiveness of republican paramilitaries compared to state forces and loyalists (as detailed in the text). There are 18 parliamentary constituencies and 26 district councils.

Table 5: Alternative clustering of standard errors

(2) of Table 5, the significance is maintained at the 1 percent level for all coefficients. In column (3) we show that the results are also robust when clustering is absent altogether.[19]

Table 6 shows that the results continue to hold when fixed effects are included or particular parts of Northern Ireland are excluded. In columns (1) and (2), we include fixed effects at the parliamentary constituency, resp. electoral district level. The magnitude and statistical significance of the estimates remains very similar to our baseline results. In column (3) the

[19] We have also checked out the sensitivity to clustering by the coordinates of the wards and on a combination of coordinates and population using a k-means clustering. Our results are robust to this.

	(1) parl. constituency level fixed effects	(2) electoral district area fixed effects	(3) dropping districts of Belfast	(4) dropping districts of Derry	(5) only districts of Belfast and Derry
Dep. Var.	all casualties	all casualties	all casualties	all casualties	all casualties
k0	9.92***	10.15***	21.92***	7.88***	8.38***
	(1.77)	(1.95)	(7.14)	(1.66)	(1.80)
k1	2.89***	1.60**	7.14***	3.47***	3.39***
	(0.43)	(0.74)	(0.78)	(0.27)	(0.29)
Mc	0.68***	1.47**	0.08	0.64***	0.65***
	(0.07)	(0.72)	(0.15)	(0.06)	(0.14)
Observations	582	582	531	552	81
R-squared	0.83	0.87	0.38	0.80	0.86

Robust standard errors in parentheses. Standard errors are clustered at the electoral district level (101 clusters). *** p<0.01, ** p<0.05, * p<0.1. "Protestant casualties" are casualties of state forces and protestants. "Catholic casualties" are casualties of catholics. "mu" is normalized to 1. "k0-k2" are decay parameters. k0 captures the transport cost of conducting attacks within the same ward. k1 captures the transport cost of conducting attacks in the direct neighbourhood of the ward. k2 captures the transport cost crossing one ward to conduct an attack. Mc captures the relative aggressiveness of republican paramilitaries compared to state forces and loyalists (as detailed in the text). There are 18 parliamentary constituencies and 101 electoral district areas.

Table 6: Fixed effects and alternative location samples

Belfast area is dropped from the sample. This was by far the most violent part of Northern Ireland with more than 850 casualties. The decay of violence across distance is still clear-cut, with $k_1 < k_0$ still holding, and both k_0 and k_1 being highly statistically significant. In column (4) we drop Derry, the second most violent area from the sample. In column (5) we include instead in the sample only the wards of Belfast and Derry. In all cases our results continue to hold. This shows that our findings are not driven by particular regions within Northern Ireland.

Further, Table 7 considers alternative time frames. Using religious group settlement patterns and violence data from the 1970s was the natural choice for the baseline regressions, as this reflects pre-conflict location decisions, which are arguably more exogenous than the people's location choices in the 1980s. Still, in Table 7 we show robustness of our main results to the inclusion of data from the 1980s. In particular, in columns (1) and (2) we use data from the 1970s and 1980s to show that parameters do not change significantly from one decade to the next. In particular, in column (1) we first estimate the same set of parameters as in the baseline regressions, but for a larger sample containing also data from the 1980s, leading to a similar overall pattern as in the baseline regressions. Then we estimate in column (2) the difference between parameters in the 1970s to 1980s.[20] To do this we run a regression in which we separate

[20] In both columns (1) and (2) we take as values for A^p and A^c the total number of fatalities in the 70s and 80s.

VARIABLES	(1) 70s and 80s pooled data all casualties	(2) 70s and 80s pooled data all casualties	(3) placebo test (80s census, 70s violence) all casualties
k0	9.56***	9.61***	-14.85
	(2.24)	(2.03)	(15.14)
k1	4.01***	3.99***	11.17***
	(0.39)	(0.31)	(1.20)
k0 change - 80s		-2.49	
		(8.78)	
k1 change - 80s		0.50	
		(1.10)	
Mc	0.68***	0.69***	0.50***
	(0.07)	(0.06)	(0.17)
Mc change - 80s		-0.19	
		(0.23)	
Observations	1,164	1,164	582
R-squared	0.75	0.75	0.67

Notes: Robust standard errors in parentheses. Standard errors are clustered at the electoral district level (101 clusters). *** p<0.01, ** p<0.05, * p<0.1. The model's parameter "mu" (determining how the recruitment of fighters relies on local population) is normalized to 1. "k0-k2" are decay parameters. k0 captures the transport cost of conducting attacks within the same ward. k1 captures the transport cost of conducting attacks in the direct (bordering) neighbourhood of the ward. Mc captures the relative aggressiveness of republican paramilitaries compared to state forces and loyalists (as detailed in the text).

Table 7: Alternative time windows

the 1970s and 1980s through two sets of spatial weight dummies. We use "k_0 in the 80s" = "k_0 in the 70s" + "k_0 change 80s" to replace for "k_0 in the 80s" in the regression equation and estimate two k_0 parameters: "k_0 in the 70s" and "k_0 change 80s". We do the same for the k_1 parameters and Mc. We do this in order to be able to conveniently test whether parameters changed from the 1970s to the 1980s, finding that coefficients are stable over time.

The fact that estimates over different decades are similar could be due to either the structure of our model applying to various periods, or, alternatively, due to the fact that population movements across Northern Ireland are limited. To discriminate between these two explanations, we perform a placebo test in column (3). Concretely, we try to explain the violence in the 1970s with settlement patterns in the 1980s. If the composition of the population is highly persistent we should find the same result as in the previous two columns, while if population movements are substantial the placebo test should generate results that are not in line with the first two columns. This is exactly what we observe in column (3), suggesting that the stability of the estimates in columns (1) and (2) is not driven by the absence of population movements. This is consistent with the view that indeed the structure of our model applies to various sub-periods of the "Troubles" in Northern Ireland.

6 Uses of the Model for Prediction

Our model builds on the assumption that the starting position of an attack is separated from the location of the attack. Given the parameter estimates of the model from the previous section, we can "invert" the model to calculate where attacks came from and which path they took. It is difficult to overemphasize the importance of this for the use of disaggregated data. The more disaggregated the data is, the more often will the location of a target and the origin of violence differ. Especially for the analysis of and response to sectarian violence taking this into account can be crucial.

In this section we first discuss where attacks came from. Then we show that the UK government has built walls to inhibit attacks exactly on those ward boundaries where our model predicts a lot of cross-border attacks. This indicates that the model captures parts of the reality of the conflict as it was perceived by its participants. Finally, we use our model to show that changes in the spatial composition of population reduced violence dramatically, despite the fact that total population did not change as much.

6.1 Predicting the Origin of Attacks

Our model enables us to compute the expected size of bilateral attacks from any ward against any other ward. Generally, we are able to calculate the number of attacks originating in a given ward j from equation (1) as

$$A_j = \tilde{F}_j^c \left(\mathbf{W}_j^c\right)' \mathbf{N}^p + \tilde{F}_j^p \left(\mathbf{W}_j^p\right)' \mathbf{N}^c. \tag{10}$$

In the simplified model in Table 4, column (1) we have estimated three parameters. From these we can calculate the number of attacks on other, contiguous wards that originated in ward j as

$$\hat{A}_j = \hat{F}_j^c \times \hat{M}_c \times \hat{k}_1^p \sum_{i \in n1(j)} N_i^p + \hat{F}_j^p \times \hat{k}_1^p \sum_{i \in n1(j)} N_i^c, \tag{11}$$

and the number of attacks that came into the ward from a different ward as

$$\widehat{cas}_j^p + \widehat{cas}_j^c = N_j^p \times \hat{M}_c \times \hat{k}_1^p \sum_{i \in n1(j)} \hat{F}_i'^c + N_j^c \times \hat{k}_1^p \sum_{i \in n1(j)} \hat{F}_i^p, \tag{12}$$

where, in both cases, we use the (fitted) number of attackers in each location is given by

$$\begin{aligned} \hat{F}_j^c &= \frac{\tilde{A}^p}{\left(\tilde{A}^c + \tilde{A}^p\right)^2}[(\hat{k}_0^c N_j^p + \hat{k}_1^c \sum_{i \in n1(j)} N_{n1(i)}^p)(N_j^c)^\mu], \\ \hat{F}_j^p &= \frac{\tilde{A}^c}{\left(\tilde{A}^c + \tilde{A}^p\right)^2}[(\hat{k}_0^p N_j^c + \hat{k}_1^p \sum_{i \in n1(j)} N_{n1(i)}^c)(N_j^p)^\mu]. \end{aligned}$$

The subtle differences between equation (11) and equation (12) illustrate the intuition of the empirical model. While casualties in equation (11) (i.e. deaths caused) are calculated by multiplying the number of fighters in ward j with the sum of potential targets in the neighborhood, casualties in equation (12) (i.e. deaths suffered) are calculated by multiplying the number of targets in ward j with the sum of fighters in the neighborhood.

Figure 8 displays for each ward on the y-axis the number of attacks originated in a given ward and on the x-axis the number of attacks suffered from in the ward. Generally more violent wards

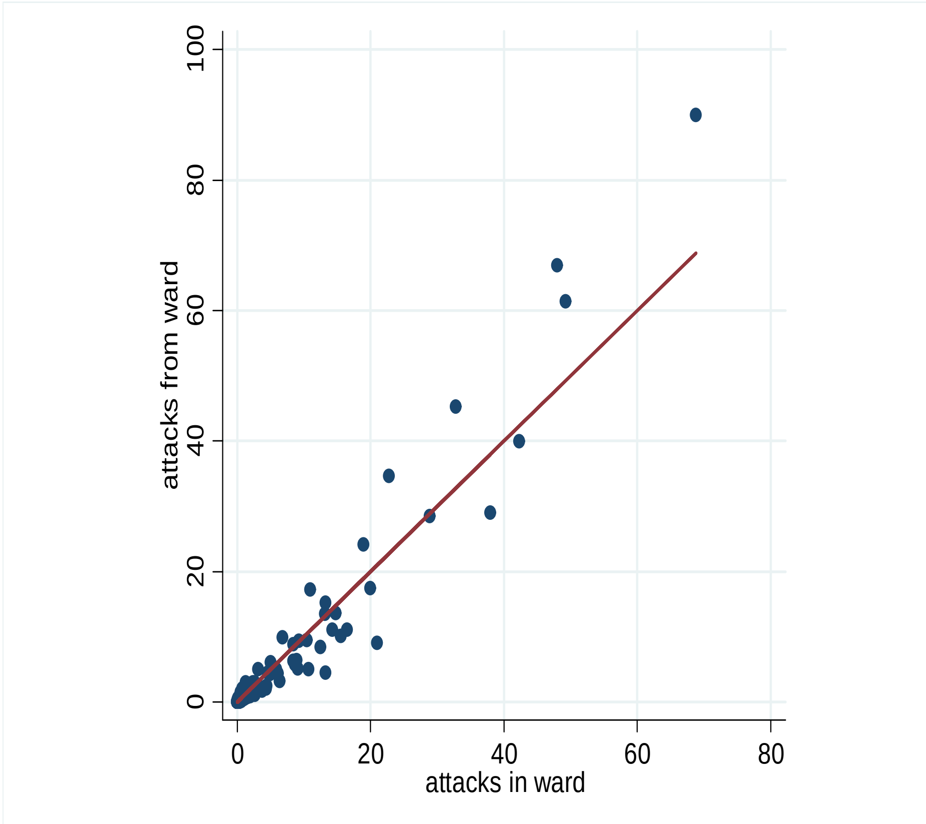


Figure 8: Origin and destination of attacks in the 1970s.

are further away from the origin. Wards with a balanced in- and outflow of attacks are located close to the 45 degree line while "net contributors" (i.e. wards that create more violence than they suffer) are located above the 45 degree line.[21]

An interesting feature of Figure 8 is that wards with low levels of violence tend to receive more attacks than they commit. However, this reverses for violent wards. This pattern is a feature of a model in which recruitment of fighters, F_j^g, is endogenous. Wards with a large population will generate higher $\tilde{F}_j^g$ and attack surrounding wards more. A smaller ward next to a larger ward will therefore become a net recipient of violence. We provide a detailed explanation of this point using simulations of the model in Appendix C.

Overall there are quite stark differences between how much violence the population in a ward

[21] If we included attacks that did not cross ward boundaries this would move points to the north-east in parallel to the 45 degree line.

causes as opposed to how much it suffers. In particular, it is not uncommon that wards receive twice as many attacks as they commit. On the other hand, the most violent ward commits about 20 casualties more than it receives.

6.2 Predicting the Location of Peacewalls

To gauge the plausibility of the model we use detailed data on the position of the barriers built by the UK government to prevent sectarian violence. Many of these walls were built directly on or close to ward boundaries. The fact that we have a full description of origins and targets allows us to predict how many attacks must have crossed each of the 1632 ward boundaries in Northern Ireland. Walls were built with the explicit goal to prevent this.

We have collected data from various sources on 36 peacewalls which were built on ward boundaries (see data description in Appendix D). We then take the estimates from column 1 in Table 4 and calculate for each of the 3,264 dyads of neighboring wards the total number of attacks crossing the boundary between them.[22] Similar to the formulas in equations (11) and (12), the formula for attacks crossing the ward boundary between ward i and j is

$$\begin{aligned}\widehat{attacks}_{ij}^{e} &= \hat{M}_c \times N_i^p \hat{k}_1^p \hat{F}_j^c + N_i^c \hat{k}_1^p \hat{F}_j^p \\ &+\hat{M}_c \times N_j^p \hat{k}_1^p \hat{F}_i^c + N_j^c \hat{k}_1^p \hat{F}_i^p.\end{aligned}$$

This variable has a mean of 0.47, a standard deviation of 2.1 and a maximum of 33. If our model is a good description of the reality in Northern Ireland we expect the UK government to build barriers where most violence crossed the ward boundary. In order to do so we use as a dependant variable a dummy indicating whether a wall was built between two wards. This variable has a mean of 0.022, i.e. there is a very low baseline risk of receiving a barrier.

In Table 8 we assess whether the number of predicted attacks using our model is able to explain the authorities' decisions to construct peace walls. In particular, we do not take the actually

[22] Each pair of wards i and j appears twice. We conduct the analysis at the dyad level in order to be able to control for ward fixed effects on both sides of the boundary. We cluster at the boundary level to rule out double-counting biasing the statistical inference.

observed attacks (which are an endogenous variable), but the expected numbers of attacks when feeding the pre-conflict population data in our structural model. Thus, all actual data underlying our explanatory variable are pre-conflict observations, addressing worries of reversed causation. Our unit of observation is the dyad, as we regress the construction of peacewalls at the border separating a ward pair on the violence flows between these two wards predicted by our structural model.

In column (1) we control for the number of Catholics and Protestants in each ward of the dyad, while in column (2) we go one step further and introduce 2 x 582 dummies to control for ward fixed effects on each side of the boundary. In other words, we check whether walls can be predicted by the expected violence interaction between two wards as our model suggests. Strikingly, across-ward boundaries predict very well on which dyad boundary peacewalls were built. The result in column (2) suggests, for example, that an increase of 10 deaths crossing a ward boundary increases the likelihood of receiving a wall by more than 50 percentage points. In other words, our model seems to indeed capture a reality which was also perceived by the government at the time - the interaction between wards is key to understand the conflict.[23]

[23] One question that arises from this is whether the construction of peacewalls on ward boundaries had the desired impact on the spatial weight parameter k_1. In order to answer this question one needs to study changes of violence across time in dyads which received a peacewall and compare them to dyads which did not receive a peacewall. Unfortunately, while we benefit from detailed data on where walls were built, we only have coarse data on the precise timing of construction, meaning that any analysis of the impact of peacewall construction may suffer from attenuation bias (e.g. treating not-yet-constructed walls as already-constructed creates statistical noise biasing estimated differences towards zero). Further, the expected violence-decreasing effect of peacewalls could also be biased towards zero by endogeneity bias (i.e. if peacewalls are constructed in places that are expected to have the largest future violence potential). With these caveats in mind, we have run regressions allowing for different k_1 in dyads separated by peacewalls (results available upon request). We find that violence dropped more at ward boundaries protected by a peacewall, but the difference is not statistically significant, which could either be due to the statistical biases discussed above or due to peacewalls proving to be by and large ineffective (i.e. many of the these barriers can be circumvented by well-equipped paramilitaries).

	(1)	(2)
Dep. Var.	Peaceline built on ward boundary	
Expected attacks over ward boundary (fitted values from structural model using pre-conflict population)	0.02**	0.05***
	(0.01)	(0.02)
population controls	yes	no
ward fixed effects	no	yes
Observations	3,264	3,264
R-squared	0.27	0.68

Notes: Robust standard errors in parentheses, clustered at the dyad level (to adjust for double-counting). *** p<0.01, ** p<0.05, * p<0.1. Regression is run on the dyad level of direct neighbours. The left hand side variable is a dummy that takes a value of 1 if a peacewall was built on the dyad boundary. "Attacks over ward boundary" is the predicted number of attacks that are taking place between the two wards in the dyad. Population controls are the number of catholics and protestants in each of the wards. Ward fixed effects control for two sets of fixed effects - one for each ward in the dyad (1164 in total).

Table 8: Predicting the location of peacewalls

6.3 Predicting the Impact of Changes in Population Localisation

Our model is also able to predict how violence evolves with changes in the composition of the population. One obvious application of this is to use the actual change of composition from the 1971 census to the 1981 census to simulate changes in violence, assuming that parameters stayed the same.

In Figure 9 below we make use of our model in the baseline Table 4 (which uses 1970s data), but now apply it to the population composition and location of the 1980s. To visualize the effect we calculate the predicted change in violence from the 1970s to the 1980s as depicted on the x-axis of Figure 9. We then compare this to the actual change in violence between the 1970s and 1980s displayed on the y-axis. Most wards are located close to the 45 degree line, highlighting the strong out-of-sample predictive power of the model. The figure also suggests that a big part of the violence reduction in the 1980s could have been due to moving decisions of the population away from the most dangerous areas.

If we interpret the correlation between changes in population and changes in violence as

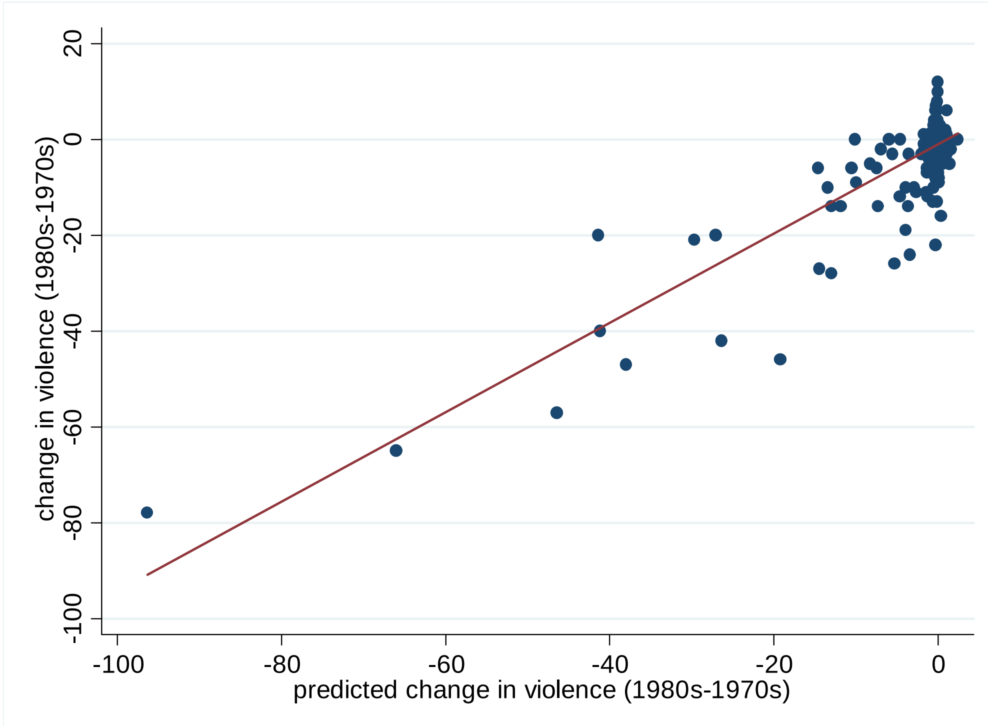


Figure 9: Out of sample predictions

causal, the population movement has saved over 600 lives.[24] The main reason for this violence reduction is that population sorted more, moving beyond the reach of perpetrators of violence - especially in wards which were very violent in the 1970s.

7 Discussion: Relevance for Other Empirical Work

7.1 Relevance for Cross-country Studies

There is an increasing body of cross-country studies of civil wars that focus on nationwide indicators of ethnic polarization or fractionalization (see Fearon and Laitin, 2003; Collier and Hoeffler, 2004; Montalvo and Reynal-Querol, 2005; Collier and Rohner, 2008; Collier, Hoeffler, and Rohner, 2009; Esteban, Mayoral and Ray, 2012). The emphasis of this literature is solely on nationwide ethnic diversity, hence neglecting all information on local ethnic diversity. As shown

[24] The interpretation is obviously to be taken with caution as the spatial weight parameters of the model may evolve over time.

in our theory the latter is important: For similar nationwide ethnic polarization scores, a country with two or three large ethnic groups that are geographically separated has lower local ethnic tensions than places where ethnic groups inhabit the same geographical areas. According to our theory, a given level of motivation at the aggregate level will lead to higher levels of violence with potential attackers and targets being closer together.

One way to illustrate this is to focus on the number of attacks in our model. All violence conducted by group g can be expressed by

$$A^g = \frac{A^{-g}}{(A^g + A^{-g})^2} RT^g,$$

where

$$T^g \equiv (\mathbf{N}^{-g})'\mathbf{W}^g diag[(\mathbf{N}^g)^\mu]\mathbf{W}^g\mathbf{N}^{-g}.$$

Taking the sum of A^g and A^{-g} yields, after reformulation, the following expression, which provides a measure of the aggregate attack potential in a country:

$$A \equiv A^g + A^{-g} = \sqrt{R\sqrt{T^g T^{-g}}}.$$

Note that our measure expresses the total predicted attacks A as a function of demographic and distance parameters only. A is strictly increasing in T^g, T^{-g}, and R. When knowing the sizes and settling patterns of the groups, one can compute predicted attacks A for all countries around the world. An important characteristic of our measure is that it is not unit-free, i.e. it explicitly takes into account different population size. This might help explain the huge variation in violence intensity across conflicts. For example, two of the most intense conflicts, Rwanda and Lebanon, are countries with diverse population groups living at close range. In contrast, India is a country with an ongoing conflict and with a very large population, but with settlement patterns that generate large distances and therefore prevent more intense violence.

A natural benchmark to compare these aggregate total attacks A to are the number of predicted attacks when distance is small. In particular, one can define a constellation where every-body is infinitely close, i.e. where for all bilateral links between people the proximity weight is maximal (k_0). Call the corresponding T^g target measure $\overline{T^g}$. In this case, the maximum attack potential becomes

$$\overline{A} = \sqrt{R\sqrt{\overline{T^g}\,\overline{T^{-g}}}}.$$

One can then define an index relating the actual availability of targets, T^g, to the maximum target availability $\overline{T^g}$ where all bilateral links have maximum proximity weight k_0. This index can be labelled as "interaction proximity" (IP) and be formally defined as

$$IP \equiv \frac{T^g T^{-g}}{\overline{T^g}\,\overline{T^{-g}}}.$$

It is easy to show that the actual predicted attacks relative to maximum predicted attacks, $A/\overline{A}$, is a monotonically increasing function of the IP index. In particular,

$$\frac{A}{\overline{A}} = \left(\frac{T^g}{\overline{T^g}}\frac{T^{-g}}{\overline{T^{-g}}}\right)^{1/4} = (IP)^{1/4}.$$

Note also that this novel IP index ranges between 0 and 1 and that one could in future work compute it for all countries with available data and run a horse-race between it and established measures such as "ethnic polarization", "ethnic fractionalization" or segregation indices on its explanatory power of recorded violence.

7.2 Relevance for Within-country Studies

In recent years there has also been a boom of articles studying civil war with the help of geo-referenced, disaggregated data, as discussed above in the literature review of Section 2. As shown by our theory, running regressions that explain local violence with only the characteristics of a given cell or district will be mis-specified when there is significant violence between these units. And, using simply existing spatial econometrics tools will not solve this problem, as the extent of such between-cell or between-district killings will depend on the interaction between relative population characteristics of the cells or districts involved. To capture the full effect of interactions across space the regression specifications need to rely on an underlying structural theory of conflict between groups.

The importance of interactions between characteristics across spatial units also seems of importance for other work inside and outside the conflict literature. There is a large number of economic decisions that are affected by the interaction of geographic features (plains next to mountains, for example). In the move towards more and more disaggregated data these interactions should receive close attention.

8 Conclusion

In this paper we have built a novel framework explaining violence as interaction across space. Neither the characteristics of a ward alone, nor the ward characteristics plus the characteristics of the neighborhood suffice to provide a powerful predictor of violence. In fact, it is the *interaction* between neighborhoods that is shown to be a prime driver of violence. As shown in the paper, our setting outperforms the predictive power of both specifications regressing violence on cell-level characteristics (i.e. assuming prohibitive transportation costs of violence) and specifications on the country level (i.e. assuming that group location does not matter and that there is no distance decay of violence).

Estimating the structural parameters of our model, we find a substantial decay of violence when crossing ward borders. In particular, the transport cost of violence is 2-6 times larger between wards than within wards. Our model is shown to generate a better fit and larger explanatory power than main alternative competing frameworks, and offers several applications. In particular, the framework allows for backing out the origin and destination of attacks, which may be particularly useful for organizing counter-terrorism activities. Finally, the setting allows for projections as well as counter-factual simulations of how group location patterns can drive current and future conflict. Further, we are able to compute for every country a summary measure of violence potential based on the group composition and location.

Several avenues seem promising for future research: First, it would be interesting to extend the model allowing for beneficial effects of inter-group interaction (e.g. with trust-building à la Rohner, Thoenig, and Zilibotti, 2013). Second, we aim to compute our aggregate measures of the attack potential and interaction proximity as a function of demographics and geography for a variety of countries and to perform a cross-country analysis of the effect of nationwide and local ethnic composition and location on conflict. Third, we warmly encourage studies that apply the current framework to the analysis of other cases than Northern Ireland and to the study of other phenomena than conflict where spatial heterogeneity of intensity and local interactions play an important role. Migration, for example, is most attractive where rich areas are close to poor areas. Other examples are research questions in regional science such as the study of urbanization patterns and local economic activity, topics in electoral politics, such as the study of local campaigning in national elections, or public health policies such as anti-AIDS campaigns.

References

[1] Anderson, James E., 1979, "A Theoretical Foundation for the Gravity Equation", *American Economic Review* 69: 106-116.

[2] Balcells, Laia, Lesley-Ann Daniels, and Abel Escribà-Folch, 2016, "The determinants of low-intensity intergroup violence: The case of Northern Ireland", *Journal of Peace Research* 53: 33-48.

[3] BBC, 2009, "Forty years of peace lines", 1 July 2009, http://news.bbc.co.uk/2/hi/uk_news/northern_ireland/8121228.stm.

[4] Behar, Alberto and Anthony Venables, 2011, "Transport Costs and International Trade", in: André de Palma, Robin Lindsey, Emile Quinet and Roger Vickerman (ed.), *A Handbook of Transport Economics*, Cheltenham UK: Edward Elgar Publishing.

[5] Belfast Interface Project, 2012, "Belfast Interfaces: Security Barriers and Defensive Use of Space", report, Belfast Interface Project.

[6] Berman, Eli, Jacob Shapiro, and Joseph Felter, 2011, "Can Hearts and Minds Be Bought? The Economics of Counterinsurgency in Iraq", *Journal of Political Economy* 119: 766-819.

[7] Berman, Nicolas, Mathieu Couttenier, Dominic Rohner, and Mathias Thoenig, 2017, "This mine is mine! How minerals fuel conflicts in Africa", forthcoming, *American Economic Review.*

[8] Besley, Timothy, and Hannes Mueller, 2012, “Estimating the Peace Dividend: The Impact of Violence on House Prices in Northern Ireland”, *American Economic Review* 102: 810-833.

[9] Besley, Timothy, and Torsten Persson, 2010, "State Capacity, Conflict and Development", *Econometrica* 78: 1-34.

[10] Besley, Timothy, and Torsten Persson, 2011, "The Logic of Political Violence", *Quarterly Journal of Economics* 126: 1411-1445.

[11] Bhavnani, Ravi, Karsten Donnay, Dan Miodownik, Maayan Mor and Dirk Helbing, 2014, "Group Segregation and Urban Violence", *American Journal of Political Science* 58: 226–245.

[12] Bhavnani, Ravi, Dan Miodownik, and Hyun Jin Choi, 2011, "Three Two Tango: Territorial Control and Selective Violence in Israel, the West Bank, and Gaza", *Journal of Conflict Resolution* 55: 133-158.

[13] Buhaug, Halvard, Lars-Erik Cederman, and Jan Ketil Rod, 2008, "Disaggregating Ethno-Nationalist Civil Wars: A Dyadic Test of Exclusion Theory", *International Organization* 62: 531-551.

[14] Bruckner, Markus and Antonio Ciccone, 2010, "International Commodity Prices, Growth and the Outbreak of Civil War in Sub-Saharan Africa", *Economic Journal* 120: 519–534.

[15] CAIN, 2015, Conflict Archive on the Internet, http://cain.ulst.ac.uk/.

[16] Caselli, Francesco, and Wilbur John Coleman II, 2013, "On the Theory of Ethnic Conflict”, *Journal of the European Economic Association* 11: 161-192.

[17] Cederman, Lars Erik, and Luc Girardin, 2007, "Beyond Fractionalization: Mapping Ethnicity onto Nationalist Insurgencies", *American Political Science Review* 101: 173-85.

[18] Collier, Paul and Anke Hoeffler, 2004, "Greed and grievance in civil war", *Oxford Economic Papers* 56: 563-95.

[19] Collier, Paul, Anke Hoeffler, and Dominic Rohner, 2009, "Beyond Greed and Grievance: Feasibility and Civil War", *Oxford Economic Papers* 61: 1-27.

[20] Collier, Paul, and Dominic Rohner, 2008, "Democracy, Development, and Conflict", *Journal of the European Economic Association* 6: 531-40.

[21] Conley, Timothy, 1999, "GMM Estimation with Cross Sectional Dependence," *Journal of Econometrics* 92: 1-45.

[22] Davidson, Russell, and James MacKinnon, 1993, *Estimation and Inference in Econometrics*, New York: Oxford University Press.

[23] Dillon, Martin, 1999, *The Dirty War: Convert Strategies and Tactics Used in Political Conflicts*, New York: Routledge Chapman & Hall.

[24] Diez Medrano, Juan, 1994, "The Effects of Ethnic Segregation and Ethnic Competition on Political Mobilization in the Basque Country, 1988", *American Sociological Review* 59: 873-89.

[25] Donaldson, Dave, 2018, "Railroads of the Raj: Estimating the Impact of Transportation Infrastructure", *American Economics Review* 108: 899-934.

[26] Dube, Oendrila, and Juan Vargas, 2013, "Commodity Price Shocks and Civil Conflict: Evidence from Colombia", *Review of Economics Studies* 80: 1384-1421.

[27] Esteban, Joan, Laura Mayoral, and Debraj Ray, 2012, "Ethnicity and Conflict: An Empirical Investigation", *American Economic Review* 102: 1310-1342.

[28] Esteban, Joan, Massimo Morelli, and Dominic Rohner, 2015, "Strategic Mass Killings", *Journal of Political Economy* 123: 1087-1132.

[29] Esteban, Joan, and Debraj Ray, 2008, "On the Salience of Ethnic Conflict", *American Economic Review* 98: 2185-202.

[30] Esteban, Joan, and Debraj Ray, 2011, "Linking Conflict to Inequality and Polarization", *American Economic Review* 101: 1345-374.

[31] Fajgelbaum, Pablo, and Edouard Schaal, 2017, "Optimal Transport Networks in Spatial Equilibrium", NBER Working Paper, 23200.

[32] Fearon, James, and David Laitin, 2003, "Ethnicity, Insurgency, and Civil War", *American Political Science Review* 97: 75–90.

[33] Grossman, Herschel and Minseong Kim, 1995, "Swords or Plowshares? A Theory of the Security of Claims to Property", *Journal of Political Economy* 103: 1275-88.

[34] Hirshleifer, Jack, 1989, "Conflict and rent-seeking success functions: Ratio vs. difference models of relative success", *Public Choice* 63: 101-12.

[35] Horowitz, Donald, 2000 [1985], *Ethnic Groups in Conflict*, Berkeley CA: University of California Press, Second Edition.

[36] Jaeger, David, and Daniele Paserman, 2008, "The Cycle of Violence? An Empirical Analysis of Fatalities in the Palestinian-Israeli Conflict", *American Economic Review* 98: 1591-1604.

[37] Jarman, Neil, 2005, "Mapping Interface Barriers", report, Institute for Conflict Research, Belfast.

[38] Kalyvas, Stathis, 2006, *The Logic of Violence in Civil War*, Cambridge UK: Cambridge University Press.

[39] Klasnja, Marko, and Natalija Novta, 2016, "Segregation, Polarization, and Ethnic Conflict", *Journal of Conflict Resolution* 60: 927-955.

[40] Kocher, Matthew Adam, Thomas Pepinsky, and Stathis Kalyvas, 2011, "Aerial Bombing and Counterinsurgency in the Vietnam War", *American Journal of Political Science* 55: 201-218.

[41] König, Michael, Dominic Rohner, Mathias Thoenig, and Fabrizio Zilibotti, 2017, "Networks in Conflict: Theory and Evidence from the Great War of Africa", forthcoming, *Econometrica*.

[42] La Ferrara, Elia, and Mariaflavia Harari, 2012, "Conflict, Climate and Cells: A Disaggregated Analysis", IGIER Working Paper n. 461.

[43] Linden, Leigh and Jonah E. Rockoff, 2008, "Estimates of the Impact of Crime Risk on Property Values from Megan's Laws", *American Economic Review* 98: 1103-1127.

[44] Lyall, Jason, 2010, "Are Coethnics More Effective Counterinsurgents? Evidence from the Second Chechen War", *American Political Science Review* 104: 1-20.

[45] Michalopoulos, Stelios, and Elias Papaioannou, 2016, "The Long-Run Effects of the Scramble for Africa", *American Economic Review* 106: 1802-1848.

[46] Montalvo, José, and Marta Reynal-Querol, 2005, "Ethnic Polarization, Potential Conflict, and Civil Wars", *American Economic Review* 95: 796-816.

[47] Morelli, Massimo, and Dominic Rohner, 2015, "Resource Concentration and Civil Wars", *Journal of Development Economics* 117: 32-47.

[48] Mueller, Hannes, 2016, "Growth and Violence: Argument for a Per Capita Measure of Civil War", *Economica* 83: 473–497.

[49] NISRA, 2006, Shapefile with location of peace lines, http://www.nisra.gov.uk/geography/Peacelines.htm.

[50] NISRA, 2015, Census Statistics, http://www.nisra.gov.uk/census/previous-census-statistics.html.

[51] Novta, Natalija, 2016, "Ethnic Diversity and the Spread of Civil War", *Journal of the European Economic Association* 14: 1074–1100.

[52] Olzak, Susan, Suzanne Shanahan, and Elizabeth McEneaney, 1996, "Poverty, Segregation, and Race Riots: 1960 to 1993", *American Sociological Review* 61: 590-613.

[53] Ploeg, Frederick van der and Dominic Rohner, 2012, "War and Natural Resource Exploitation," *European Economic Review* 56: 1714-1729.

[54] Plümper, Thomas, and Eric Neumayer, 2010, "Model Specification in the Analysis of Spatial Dependence," *European Journal of Political Research*, 49: 418-442.

[55] Rohner, Dominic, 2011, "Reputation, Group Structure and Social Tensions", *Journal of Development Economics* 96: 188–199.

[56] Rohner, Dominic, Mathias Thoenig, and Fabrizio Zilibotti, 2013, "War Signals: A Theory of Trade, Trust and Conflict", *Review of Economic Studies* 80: 1114-1147.

[57] Rohner, Dominic, Mathias Thoenig, and Fabrizio Zilibotti, 2013b, "Seeds of Distrust: Conflict in Uganda", *Journal of Economic Growth* 18: 217-252.

[58] Sambanis, Nicholas, 2000, "Partition as a Solution to Ethnic War: An Empirical Critique of the Theoretical Literature", *World Politics* 52: 437-83.

[59] Schutte, Sebastian, and Nils Weidmann, 2011, "Diffusion patterns of violence in civil wars", *Political Geography* 30: 143-152.

[60] Shakarian, Paulo, and V.S. Subrahmanian, 2011, *Geospatial Abduction: Principles and Practice*, Berlin: Springer.

[61] Skaperdas, Stergios, 1992, "Cooperation, Conflict, and Power in the Absence of Property Rights", *American Economic Review* 82: 720-39.

[62] Spolaore, Enrico, and Romain Wacziarg, 2016, "War and Relatedness", Review of Economics and Statistics, 98(5): 925-939.

[63] Sutton, Malcolm, 1994, *Bear in Mind these Dead ... An Index of Deaths from the Conflict in Ireland* 1969-1993, Belfast: Beyond the Pale Publications.

[64] Townsley, Michael, Shane Johnson and Jerry Ratcliffe, 2008, "Space Time Dynamics of Insurgent Activity in Iraq", *Security Journal* 21: 139-146.

[65] US Army, 2006, "Counterinsurgency. Field Manual No. 3-24", Headquarters Department of the Army.

[66] Varshney, Ashutosh, 2001, "Ethnic Conflict and Civil Society: India and Beyond", *World Politics* 53: 362-98.

A Changes in Transport Costs

Our model allows us to analyse how much violence is driven by cross-border attacks. A way to understand this is to set $k_1 = 0$ in our model from equation (9) but keep everything else constant. Figure 10 below shows what would happen in the 12 most violent wards.

As a point of departure we take our estimates from equation (9) to generate fitted values. In the most violent ward we predict 100 casualties in the 1970s, in the second most violent ward 65 casualties, and so on (light grey bar). As a first step we then set $k_1 = 0$, but only in the part of the equation that describes the effectiveness of attacks across boundaries, i.e. we generate fitted values according to

$$\widehat{cas}_j^e = \hat{M}_c \times N_j^p \hat{k}_0^p \hat{F}_j^{\prime c} + N_j^c \hat{k}_0^p \hat{F}_j^p, \tag{13}$$

but assume that $\hat{F}_j^{\prime c}$ and $\hat{F}_j^p$ stay the same. This implies that the motivation to fight in all wards is maintained but that there are no attacks across ward boundaries. There is a drastic decrease in expected attacks in this thought experiment (dark grey bar). Attacks are reduced by more than half. This illustrates the salience of cross-border attacks that our model predicts for the Northern Irish conflict. A model which does not take the composition of the neighborhood into account would miss this violence and instead attribute it to interactions within the same geographic unit.

As a next step we set $k_1 = 0$ everywhere in equation (9).[25] This also shuts down the recruitment motivation effect of cross-ward targets (and hence lowers $\hat{F}_j^{\prime c}$ and $\hat{F}_j^p$), leading to an even sharper drop in casualties (black bar). The point of this exercise is to demonstrate that motivation is an important factor. The reduction of violence from dark grey to black bars is again very substantial.[26]

Taken together, Figure 10 highlights the incentives for policy makers to reduce movements of people in situations with high-levels of acute violence. Depriving fighters of potential targets can

[25] This would yield the expression $\widehat{cas}_j^e = \hat{M}_c \times N_j^p \frac{A^p}{(A^c+A^p)^2} \hat{k}_o[(\hat{k}_o N_j^p)(N_j^c)^\mu] + N_j^c \frac{A^c}{(A^c+A^p)^2} \hat{k}_o[(\hat{k}_o N_j^c)(N_j^p)^\mu]$.

[26] In Appendix C we simulate the effect of composition on violence into and out of a ward of 2,000 inhabitants in a neighborhood of 20,000 inhabitants. This exercise stresses the importance of motivation for violence levels.

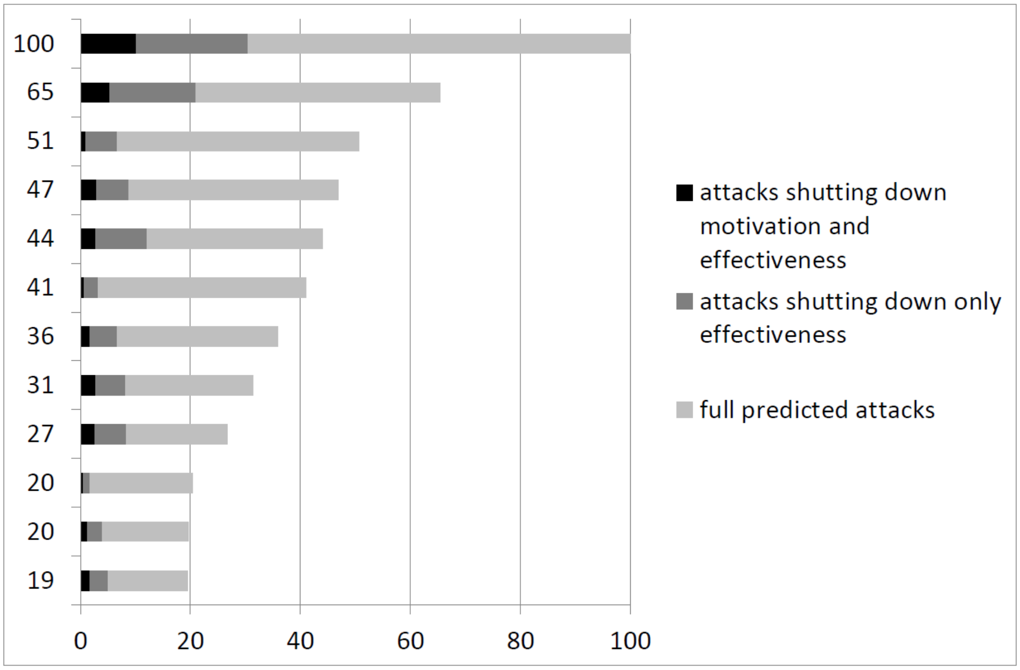


Figure 10: Counterfactual with $k_1 = 0$

have large effects on violence in the short-run.[27]

B Further robustness checks and results

In this appendix we include two additional tables that are discussed in more detail above in the main text. In particular, Table 9 below replicates Table 2, but using in each column the value of μ that in a maximum likelihood grid search maximizes the overall fit of the model.

Further, Table 10 runs in column (1) an alternative specification for generating Figure 6 in the main text, while column (2) performs another commonly used alternative specification.

[27] This result refers to the fighting intensity during conflict. In contrast, in post-conflict reconstruction, fostering interaction and "building bridges" between communities may be important (see Rohner, Thoenig, and Zilibotti, 2013).

VARIABLES	(1) protestant casualties	(2) protestant casualties	(3) catholic casualties	(4) catholic casualties
mu	1.04	1.18	0.78	0.87
k0	10.49***	8.17***	11.97***	10.78*
	(0.82)	(1.04)	(2.80)	(5.62)
k1	1.74***	1.05***	3.76***	2.01
	(0.11)	(0.37)	(0.59)	(2.59)
k2		0.42		0.94
		(0.29)		(0.91)
Observations	582	582	582	582
R-squared	0.61	0.62	0.76	0.77

Notes: Robust standard errors in parentheses. Standard errors are clustered at the electoral district level (101 clusters). *** p<0.01, ** p<0.05, * p<0.1. "Protestant casualties" are casualties of state forces and protestants. "Catholic casualties" are casualties of catholics. "mu" is the parameter of the model that determines how the recruitment of fighters relies on local population and is chosen in a grid search so as to maximize the R squared for each specification. "k0-k2" are decay parameters. k0 captures the transport cost of conducting attacks within the same ward. k1 captures the transport cost of conducting attacks in the direct (bordering) neighbourhood of the ward. k2 captures the transport cost of crossing one ward to carry out an attack.

Table 9: Grid search of mu

VARIABLES	(1) casualties	(2) casualties
protestants (in 1000)	2.03***	
	(0.41)	
catholics (in 1000)	2.20***	
	(0.39)	
protestants (in 1000) * catholics (in 1000)	0.29***	
	(0.03)	
share of catholics		8.01
		(5.44)
share of catholics squared		-7.70
		(4.68)
Observations	582	582
R-squared	0.69	0.01

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Alternative model with violence potential fully decaying in distance

C Simulation of Violence in and out of Wards

Our model allows us to represent graphically in what type of environment a given ward is most likely to "send" or "receive" violence. In what follows we simulate a ward (ward 1) of 2000 inhabitants in a neighborhood of 20000 inhabitants - this is roughly a ward of average size in a neighborhood of average size. To simplify the analysis we assume that the neighborhood consists of only one ward (ward 2). We will use our estimated model to distinguish between attacks into the ward and attack originating from the ward. Note that all attacks into ward j from i are given by

$$\begin{aligned} casin_j &= \frac{\tilde{A}^p}{\left(\tilde{A}^c+\tilde{A}^p\right)^2} N_j^p \times \hat{M}_c \hat{k}_1^p \times (\hat{k}_0^p N_i^p + \hat{k}_1^p N_j^p)(N_i^c)^\mu \\ &+ \frac{\tilde{A}^c}{\left(\tilde{A}^c+\tilde{A}^p\right)^2} N_j^c \times \hat{k}_1^p \times (\hat{k}_0^p N_i^c + \hat{k}_1^p N_j^c)(N_i^p)^\mu, \end{aligned} \tag{14}$$

whereas attacks from ward j over the ward boundaries are given by

$$\begin{aligned} casout_j &= \frac{\tilde{A}^p}{\left(\tilde{A}^c+\tilde{A}^p\right)^2} (N_j^c)^\mu (\hat{k}_0^p N_j^p + \hat{k}_1^p N_i^p) \times \hat{M}_c \hat{k}_1^p \times N_i^p \\ &+ \frac{\tilde{A}^c}{\left(\tilde{A}^c+\tilde{A}^p\right)^2} (N_j^p)^\mu (\hat{k}_0^p N_j^c + \hat{k}_1^p N_i^c) \times \hat{k}_1^p \times N_i^c. \end{aligned}$$

We first focus on the simulation of attacks on individuals in ward 1 from ward 2, depending on the population composition in the two wards.[28] Figure 11 depicts the number of attacks into ward 1 on the z-axis, and the composition of the population in ward 1 and ward 2 on the other two axis. The axis P1 captures the composition of ward 1. If $P1 = 0$, all $2,000$ inhabitants in ward 1 are assumed to be Catholics. If $P1 = 2,000$, all are Protestants. Analogously, if $P2 = 0$, all $20,000$ inhabitants of the neighborhood (ward 2) are assumed to be Catholics, while if $P2 = 20,000$, all are assumed to be Protestants.

Assume first $P1 = 0$ and $P2 = 0$. There are only Catholics living in both wards and there

[28] We take $\frac{A^c}{(A^c+A^p)^2}$ and $\frac{A^p}{(A^c+A^p)^2}$ from observed fatalities and assume $\mu = 1$. We then use the estimated coefficients $M_c = 0.63$, $k_o = 8.30$ and $k_1 = 3.45$ from our main results of Table 4, column (1).

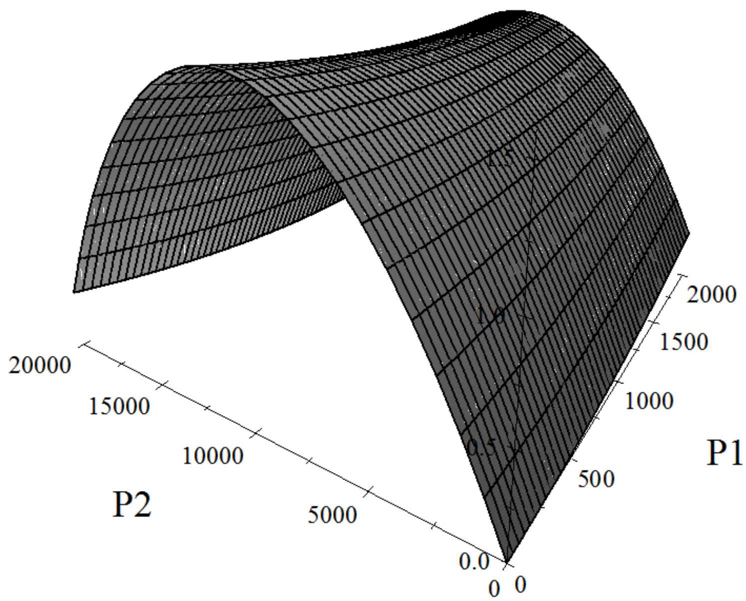


Figure 11: Simulation of attacks against ward 1

are therefore no attacks on individuals in ward 1. Fix $P1 = 0$ and increase P2. The result is an inverted U-shape in attacks on the ward 1. Why do attacks from outside take this shape? The key to understanding the decrease in attacks despite the increasing number of Protestants in ward 2 is the fact that attacks are driven both by the number of Protestants living close by and by their motivation to engage in conflict. If $P2 = 20,000$, there are no Catholics in ward 2 so that the Protestants in ward 2 are much less motivated to engage in violence (i.e. there are fewer potential targets at close range). If, however, $P2 = 10,000$, then there are a lot of targets which leads to more fighters per Protestants in ward 2. If we fix $P2 = 0$ we get an increase in violence with a rise in $P1$ because more targets are available in ward 1.

In contrast, Figure 12 focuses on the violence originating in ward 1. Again, fix $P1 = 0$ and increase $P2$. Now there is a convex relationship between violence and P2, driven by the increased motivation due to more targets. The rising number of targets together with the rising motivation leads to the convexity. Interestingly, the relationship is not convex if one fixes $P2 = 0$ and increases $P1$ instead, as there is now a trade-off that kicks in when Protestants become the majority in ward 1. They are exceedingly "demotivated" by the lack of targets (Catholics) within-ward.

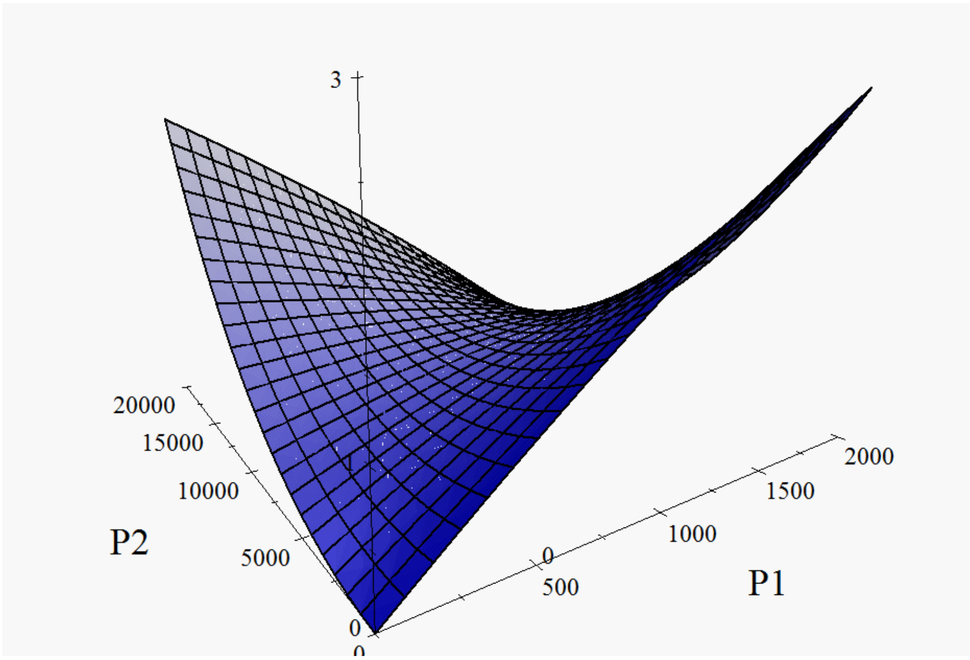


Figure 12: Simulation of attacks originating in ward 1

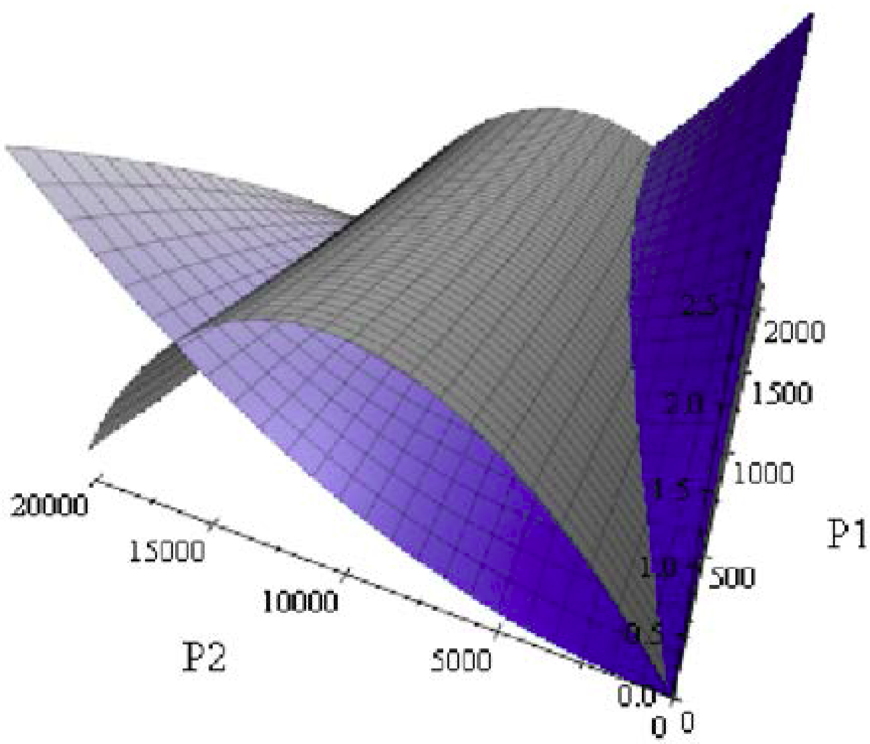


Figure 13: Simulation combining the outflow and inflow of attacks in ward 1

In Figure 13 we combine the two previous figures. We can now grasp the determinants of a ward becoming a net contributor to violence. In a nutshell, wards become net contributors to violence if they are in a very homogenous surrounding with either only Protestants or Catholics. The reason is that there are a lot more targets for inhabitants of ward 1 in this situation.

D Data on Peacewalls

First, we have collected data on the location of the peace lines. For this we drew on various lists of peace lines containing geographical information (Jarman, 2005; BBC, 2009; Belfast Interface Project, 2012), on the geo-referenced map of peace lines from NISRA (2006) and on correspondence with the Department of Justice of Northern Ireland, which provided us with additional information in response to our freedom of information request DOJ FOI 12/136.

Combining all this sources and using a geo-referenced map of all wards of Northern Ireland, we have been able to put together a novel dataset on the location of peace lines. Peace lines running parallel to borders between two wards and lying either directly on the ward border or in-between the ward border and the nearest street are counted as peace lines separating two wards. Peace lines located in only one ward and not meeting the above criterion are counted as within-ward peace lines. We have not encountered problematic cases that could not be associated to neither of the two categories above (i.e. there have not been peace lines running perpendicular to ward borders and crossing them etc).