The Legacy of Conflict: Regional Deprivation and School Performance in Northern Ireland

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Abstract

"The Troubles" was a long-run, low-intensity conflict that occurred in Northern Ireland from 1969 until 1998, exhibiting regular but small-scale terrorist attacks. Little is known about the consequences of the conflict and of the peace process that resulted in the signing of the Good Friday Agreement in 1998. Combining detailed data on terrorist violence with the Northern Ireland Multiple Deprivation Measure and primary school level data from the national, standardised Key Stage II exams for the years 1998/1999 to 2008/2009, we analyse the legacy of the conflict on school performance. We identity the causal effect of regional deprivation on average pass rates using an error component two-stage least squares model which accounts for endogeneity and selection. As children of primary school age within our same were educated after the end of the conflict, regional variation in conflict intensity can be used to instrument deprivation. We find that schools located in deprived regions perform significantly poorer than those in other regions. The findings suggest that regional social inequality is correlated with historical conflict intensity. This persistence calls for policy measures to overcome these long-run effects.

Keywords: Violent Conflict, Regional Deprivation, Human Capital Accumulation, Northern Ireland

JEL classifications: I24, R23

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1 Introduction

Tension between Protestants and Catholics are still going on in Northern Ireland. In summer 2012, individuals from both groups riot again in Belfast. These tensions are routed in "The Troubles", a conflict that was most violent in the years between 1969 and 1994 and officially ended with the ceasefires in 1998, when the Good Friday Agreement was accomplished. The riots that can be observed nowadays are not comparable to the terrorist attacks that accompanied the country for so many years, but they are related.

Responsible for an excess of 3,500 deaths, unequally spread across Northern Ireland (Figure 1), the conflict was the result of decades of simmering ethnic differences between the broadly Protestant Unionists, who supported the union between Northern Ireland and Great Britain and predominantly Catholic Nationalists, who sought a unified, independent Ireland. The main actors in this conflict can be disaggregated into the main paramilitary players (Loyalists and Republicans) and the main political players (Unionists and Nationalists). Broadly speaking Loyalists and Unionists were drawn from the protestant population of Northern Ireland, whilst a significant majority of Republicans and Nationalists were drawn from the catholic population. It should be noted that whilst cultural identity and nationalism played important roles in the conflict, the real and perceived horizontal inequalities between the two communities are frequently cited as the casus belli of the conflict (Fitzduff and O'Hagan, 2009). Whilst the violence largely ended almost 20 years ago, however, many of the scars of the conflict are still visible in the country. The Protestant and Catholic communities remain divided, with ethnic separation, fear and occasional death still features of the landscape. We use this continued legacy of conflict and its association with deprivation to shed light on the relationship between parents' economic status, income and children's educational outcomes.

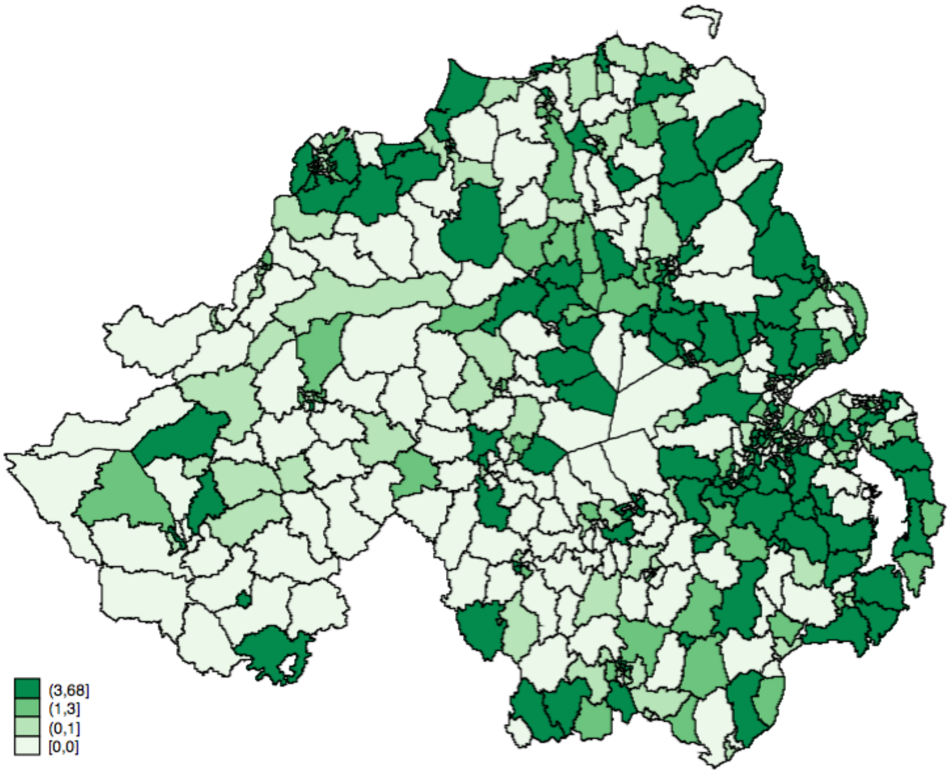
In detail, we study the effect of regional deprivation on primary school outcomes. Although it is known that education plays an important role for child / adolescent development and future labour market outcomes, the topic has received little attention so far (Gibbons, 2002). To our best knowledge, no study exists which investigates this relationship for Northern Ireland. Apart from the importance of schooling for a life without poverty, knowing about the regional differences and effects of deprivation on school outcomes is important to prevent regional and horizontal inequality and perceived discrimination among adolescents who are the main actors in the latest riots in Belfast.

The regional deprivation measure used is the Northern Ireland Multiple Deprivation Measure (MDM) from 2005. This measure captures the regional differences of latent neighbourhood quality or wealth as it consists of different deprivation domains. The data are matched to school level data of all primary schools in Northern Ireland between 1998/199 and 2008/2009. Exploiting a dataset of deaths pertaining to “The Troubles” in Northern Ireland by Sutton (1994), that has been geographically mapped to Northern Ireland’s 582 electoral wards by Ferguson (2012), we implement an error component two-stage least squares regression analysis. Results in the first-stage regression show the strength between historical terrorist violence in a ward and its current level of deprivation but we note that, over and above this impact on deprivation, there is no further relationship between violence and educational outcomes. Consequently, in the second stage, we show the impact of deprivation on primary school performance.

Our modelling strategy and data overcomes most issues of selection by accounting for region-specific effects, whilst the exogeneity of our violence instrument prevents potential endogeneity bias. Typically, the literature looks at poverty and its related proxies as a potential measure other unobservable neighbourhood effects. We show that, over and above these neighbourhood-level unobservables, deprivation still plays a significant role in the determination of educational outcomes.

The rest of this paper is set out as follows: in the next section, we discuss and review the literature relevant to this project. In section three, we discuss the data we use. In section four, we discuss our methodology, in section five we introduce our results and in section six we conclude.

Figure 1: Number of Conflict-related Deaths by Wards between 1969 and 1994 in Northern Ireland



Source: Authors' construction using data by Sutton (1994).

2 Background

In economic research, there is a long-standing and well-accepted dictum that an individual's level of education has obvious and positive impacts on his / her income. Indeed, this notion provides the essential backdrop of Spence's (1973) famous signalling model. Highly productive individuals educate themselves in order to signal their capabilities to potential employers who, accordingly, pay a premium for their service. Of course, this isn't an idea that has simply been plucked from thin air. Significant empirical work has confirmed these ideas – or at least, the idea that individuals with higher education tend to earn more than their poorly educated counterparts.

Whilst few would disagree with this notion, it does raise important questions about social-mobility and causality. Dealing with these questions in turn, we consider the notion that if education improves future labour market outcomes, then education itself becomes an important anti-poverty tool. The potential of a bi-directional relationship between these two effects, however, is explored as early as Tolley and Olsen (1971) who discuss the relationship between regional income and local governments' ability to spend on education. If, for example, low parental income adversely impacts on their children's education outcomes, then children from poorer backgrounds face a greater risk of facing continued poverty in the future. Such a relationship between education and familial income has proven to be a recent source of interest for economists (Dahl and Lochner, 2008, for example).

Taking the well-established notion of the intergenerational transfer of human capital as a baseline, significant work has looked at the role of familial income and parental socio-economic class on the life opportunities and outcomes of their children. Measuring the socio-economic class of an individual's parents is no easy task, however. Accordingly, the literature has turned to proxies in order to discuss this effect. Proxies used include parental education (Cremer et al., 2003), income (Blau, 1999), occupation (Oreopoulos and Stevens, 2008) and area of residence (Weinhardt, 2010).

Sociological musings shed light on some of the potential underlying causes of such a relationship. Children from poorer backgrounds may, for example, lack access to the internet or other learning resources. Children from wealthier backgrounds can play a more direct role in selecting the school to attend and so on. Economic logic, too, can be applied, however. For example, are expectations on the returns to education the same across economic-strata? Does the concept of opportunity cost play a role – is two years of foregone income a different consideration to those from richer or poorer backgrounds? A final strand of this literature shows that impacts can occur through health / mental health channels, with associations between income and health well-established (McLoyd, 1990, for example).

Along the lines of Dahl and Lochner (2008), we argue that income, itself, may be endogenous to the process. Individuals from poorer backgrounds may face adverse home situations, for example, that do not necessarily improve should the family become exogenously richer. Thus, both children's opportunities and family income are influenced by the same underlying factors.

Whilst the relationship between education and income has been a well-established part of the economics literature throughout the 20th century, the question about how family income can impact on a child's well-being or outcomes is a relatively more recent literature. Although the earliest idea that income could impact on education, as well as vice versa, was explored as early as the 1970s (e.g. Tolley and Olsen, 1971). These papers looked at direct economic effects, such as high income areas generating higher levels of local taxation that could then be spent on local schools. More recently, McLoyd (1990) looks at the relationship between poor parental (mental) health and children's outcomes, whilst a more recent array of literature from the mid-1990s onwards looks at the direct role of parental, familial and regional income. Fuller reviews of the literature from this era can be found in the surveys of Haveman and Wolfe (1995) and Mayer (1997).

As noted in these surveys, the earliest literature presents only correlation evidence, rather than inferring causality. A number of endogeneity and missing-variables issues appear throughout these works. In order to present causal evidence, the likes of Duncan and Smith (1998), Blau (1999) and Levy and Duncan (2000) introduce fixed effects estimations to control for unobservables at the level of the unit of analysis. Blau finds that permanent income effects, such as historical wealth, have larger effects than current family income. Duncan and Smith (1998) and Levy and Duncan (2000) find that it is family income in the earliest years of life that has the most profound impacts.

More recently, Duncan (2011) and Milligan and Stabile (2008) use government income transfers as a natural experiment to test the impact of family income on education attainment, with both finding positive relationships between family income and educational outcomes. Another bulk of literature has used another natural experiment, created by the Norwegian oil boom, to test the same hypothesis. Working on the notion that, with an initially uneven distribution of the positive income benefits of this boom across Norway, certain parents income "exogenously" rose, which did not reflect any increase in their innate abilities. Løken (2010) and Løken et al. (2012) show pronounced positive impacts of increased income on school attainment amongst low income families but the effect is less pronounced for richer families, suggesting a diminishing return of the effects.

A second notion from the literature that is also important for the analysis we present is the role of neighbourhood effects, which suggests that it is not necessarily the impact of poverty, itself, that affects outcomes but that poverty is associated with a number of other neighbourhood characteristics that also impact on educational outcomes. Weinhardt (2010), for example, looks at the effect of living in a deprived neighbourhood on educational outcomes. Using the percentage of high-density social housing as a proxy for deprivation, Weinhardt (2010) defines the timing of movement into these neighbourhoods as the causal feature but shows no negative effects on those who moved into deprived neighbourhoods earlier than those who moved more recently.

Oreopolous (2003) also shows no long-term effects from a quasi-experimental approach using social housing building projects in Toronto, whilst Jacob (2004) uses demolitions in Chicago as a proxy for deprivation, finding that those affected by demolitions do not have worse outcomes than those who are not affected. School quality effects are also discussed by the likes of Durlauf (1996) and Gibbons and Silva (2008).

Contrary to these findings, however, Bayer and Topa (2008) suggest negative regional impacts, discussing 'network effects' as their transmission mechanism. These outcomes are supported by Davis-Kean (2005) in the psychology literature. In the economics literature, Cutler and Glaeser (1997) use physical and geographic features as an instrument for neighbourhood quality and show negative effects on outcomes, whilst Goux and Maurin (2007) also show negative impacts using the dates of birth as an inventive proxy for neighbourhood quality and noting the role of selection into neighbourhoods; poorer families have less choice over where to live and, therefore, have less access to the best schools. This notion is also supported by Gibbons and Silva (2008).

Bayer and Ross (2006) use a regression on neighbourhood house prices as a control for neighbourhood quality and show both small negative impacts from neighbourhood quality and, perhaps more tellingly, larger negative impacts than from OLS regressions. Gibbons and Silva (2008) suggest poorer outcomes for those from less wealthy backgrounds. In another sphere, Bauer et al. (2011) suggest negative impacts on personal employment probabilities from neighbourhood unemployment, using a similar methodology to Bayer and Ross (2006).

In the specific context of Northern Ireland, the authors are aware of only Shuttleworth (1995) and Shuttleworth and Daly (1997) who look at the outcomes of individuals in Northern Ireland and of the role of "The Troubles" in their educational outcomes and Cummings et al. (2011), who look at the relationship between violence and children's "adjustment problems", which can easily be extrapolated to our question; poorly adjusted children seem less likely to achieve well in school, compared to their better adjusted counterparts.

Our paper aims to build on the ideas introduced in these two strands of literature. Whilst our specific interest is in the role of neighbourhood deprivation, a number of the issues raised in the individual-level literature carry important connotations for this work.

3 Data

For the empirical analysis we combine data from different sources. We extracted data from The Northern Ireland Department of Education[1] on all primary schools in Northern Ireland for the academic years 1998/1999 to 2008/2009. Based on school names we pool the cross sections to construct a panel data set in which schools are the unit of observation. Due to teacher strikes data is not available for the year 2002/2003 and for a few schools data is not complete in all years. We exclude preparatory schools. This results in an unbalanced panel of $n = 751$ primary schools over $T = 10$ academic years, hence $n \times T = 6226$ school-year observations. We have information on average Key Stage II exam results, whether the school offered exams in Gaelic language, the number of pupils per school and the teacher-pupil ratio.[2] Key Stage II exams are formal tests taken

[1] http://www.deni.gov.uk

[2] The role of school quality, for example, may be an important driver of our outcomes. Similarly, school culture may also have important effects on our outcomes. Therefore, for future analysis we would

by pupils at the end of primary school (approximately age 11) in English (or Gaelic) and Mathematics. The average pass rate measured by Key Stage II exams by school and by year is a proxy for school performance and serves as the outcome variable that we want to analyse.

In particular, we are interested in the relationship between regional deprivation and school performance. Our regional deprivation measure is the Northern Ireland Multiple Deprivation Measure (MDM) from 2005 provided by the Northern Ireland Statistics and Research Agency and obtained by the Social Disadvantage Research Centre at the University of Oxford.[3] The MDM are official spatial deprivation measures on different domains of social and economic wellbeing, namely income deprivation, employment deprivation, health deprivation and disability, education, skills and training deprivation, proximity to services deprivation, living environment deprivation and crime and disorder. Each deprivation domain was measured in 2003 and denominated by population size as in the 2001 Census.[4] In our analysis we construct an overall deprivation measure which consists of the average of the income domain, the employment domain, the health domain, the living environment domain and the crime and disorder domain. We exclude the education domain as it consists of indicators which are likely to predict Key Stage II exam results. Furthermore, we exclude the proximity to service domain as road distances to different service points, e.g. general practitioners and food shops, as are likely to be predictors of proximity to primary school.

We chose as a level of geographical disaggregation electoral wards. A smaller level of disaggregation, such as Super Output Areas, is not feasible since they are not possible to be matched to the school level data. Super Output Areas were introduced with the 2001 Census and the school data dates back to 1998. However, the available level of disaggregation is not a drawback in our analysis as each ward is inhabited by only 1.9 primary schools on average.

Data on violence is taken from Sutton (1994). The database provides detailed information on killed individuals due to "The Troubles" between 1969 and 1994. We construct a variable called *deaths* which is the number of deaths between 1969 and 1994 per ward. Table 1 provides summary statistics on conflict intensity. It can be seen that the number of deaths per ward ranges from 0 to 81 and has a mean of 4.65. In 61% of all wards at least one death occurred, in 25% of all wards more than 5 incidents occurred and in 15% of all wards more than 10 incidents occurred. We have also divided the number of deaths by the population size in 2001. This variable is a proxy for actual deaths per inhabitants at the time of incident.

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like to include attendance rates and the share of pupils eligible to free meals.

[3]http://www.nisra.gov.uk/deprivation/update_of_nimdm_2005.htm

[4]See NISRA (2005) for more details.

Finally, we have data on the total number of bombings and the total number of shootings between 1998 and 2010. These data are disaggregated at District Crime Units (DCU) of which 30 exist in our data. This low level of disaggregation explains the high number of incidents after the Good Friday Agreement. These numbers count all kinds of violent attacks that have been reported to the polics.

Table 1: Descriptive Statistics Violence Data

	Mean	Std.Dev.	Min	Max
No. of Deaths by Ward	4.65	8.87	0	81
Deaths per 1,000 inhabitants	1.57	2.94	0	25
No. of Deaths ≥ 1	0.61	0.49	0	1
No. of Deaths ≥ 5	0.25	0.43	0	1
No. of Deaths ≥ 10	0.15	0.35	0	1
Shooting Incidents by DCU	3.65	10.32	0	152
Shooting Incidents by DCU	5.80	11.34	0	111
N	6226			

Note: Authors' calculations based on Sutton 1994.

Table 2 provides summary statistics on the constructed overall MDM score, the school level variables and populations size by ward and age. The descriptive statistics are provided for two samples: Schools which are located in areas of high violence and schools which are located in areas of low violence. We define high violence areas as those in which at least five deaths occurred.

Table 2: Descriptive Statistics School Data

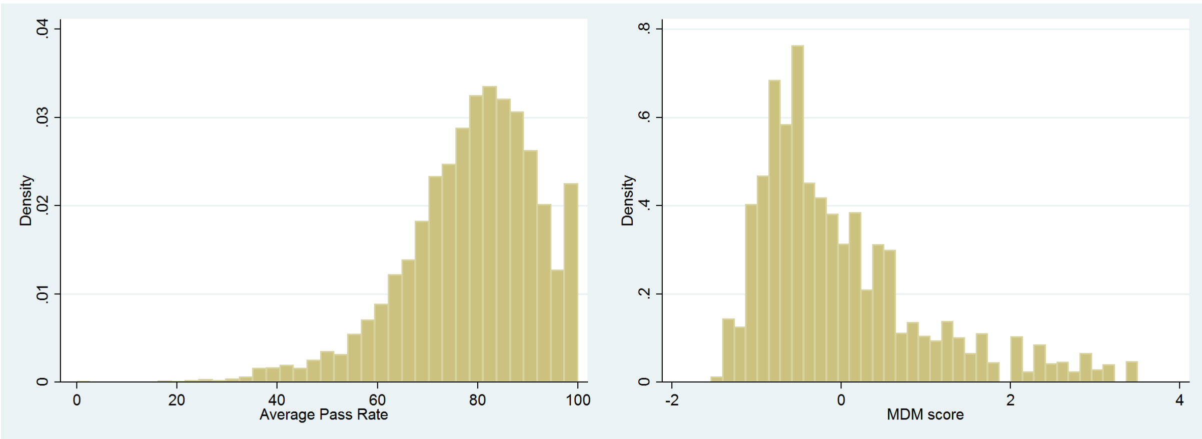
	Low Violence Area		High Violence Area		Difference	
	Mean	Std.Dev.	Mean	Std.Dev.	Diff.	Std.Dev.
Average Pass Rate	79.32	(12.84)	77.47	(14.38)	0.52	(0.35)
Number of Pupils	30.2	(23.88)	29.1	(21.68)	1.4**	(0.6)
Ratio of Teachers to Pupils	19.53	(3.14)	19.42	(2.96)	0.11	(0.08)
Gaelic Speaking School	0.00	(0.06)	0.01	(0.10)	-0.01***	(0.00)
All Persons 0-15	675.80	(316.64)	751.83	(323.82)	-39.10***	(8.31)
All Persons 16-39	919.2	(477.85)	1059.1	(747.41)	-75.9***	(14.6)
All Persons 40-59/64	807.68	(298.30)	842.92	(300.92)	-12.52	(7.79)
All Persons 60/65+	459.18	(174.76)	497.53	(220.15)	-26.29***	(4.88)
MDM score	7.70	(4.36)	9.91	(5.89)	-1.48***	(0.13)
N	2413		1569		6226	

Note: Authors' calculations based on Key Stage II data and Sutton (1994). In a 'High Violence Area' more than 5 deaths occurred.

In low violence areas average pass rates possess a mean of 79.3 whilst in high violence areas the mean is 77.5. This difference is not statistically significant at this level of division. In those areas in which more than 10 incidents occurred the mean of average pass rates is 74.9. High violence areas are bigger in terms of population size and possess a statistically significant higher level of deprivation. The MDM score is 9.9 in such areas and 7.7 in low violence area. Figure 2 shows the distribution of average pass rates and the MDM score. The MDM score is standardised with mean zero and a standard deviation of one. In Figure 3 we provide Kernel density plots of average pass rates for high and low conflict areas separately. It can be seen that with increasing violence intensity the density plots diverge, with higher density of high pass rates in low intensity conflict areas.

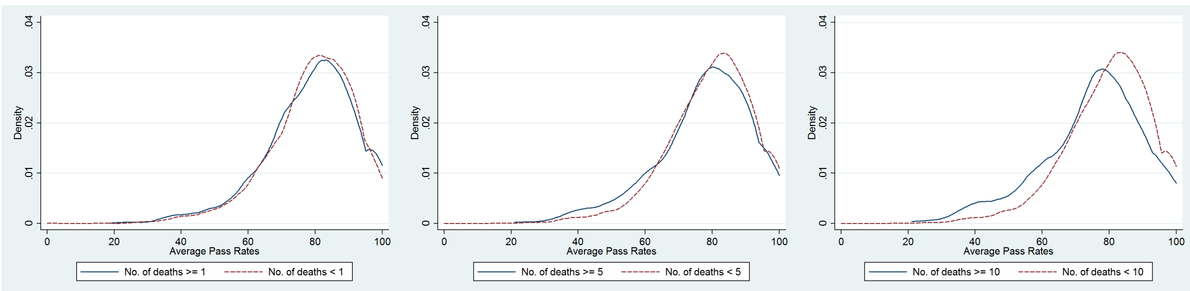
These descriptive statistics provide evidence for a strong correlation between regional deprivation and bad school outcomes. To identify the causal effect, we use regression analysis as explained in the following section.

Figure 2: Average Pass Rates and MDM Score Density



Source: Authors' construction.

Figure 3: Average Pass Rates Density by Violence Intensity



Source: Authors' construction.

4 Methodology

The unconditional relationship between regional deprivation and school performance as shown in the descriptive statistics is negative. The reasons for this phenomenon can be diverse though. It can be imagined, that in deprived regions which exhibit high unemployment, low levels of income, low health standards, high crime rates and a bad living

Table 3: Correlation between Deprivation Scores

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) MDM score	1.000					
(2) Income Domain Score	0.650	1.000				
	(0.000)					
(3) Employment Domain Score	0.645	0.930	1.000			
	(0.000)	(0.000)				
(4) Health Domain Score	0.744	0.707	0.721	1.000		
	(0.000)	(0.000)	(0.000)			
(5) Education Domain Score	0.622	0.789	0.800	0.644	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)		
(6) Living Environment Domain Score	0.681	0.659	0.647	0.552	0.647	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
(7) Crime and Disorder Domain Score	0.870	0.408	0.409	0.599	0.381	0.233
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

environment, inhabitants also have lower education levels than in less deprived regions. In fact, the correlation between these different deprivation domains are highly correlated with the education deprivation domain as can be seen in Table 3. The education deprivation domain captures the educational level of adults and adolescents in an area. As is known from the literature on the intergenerational transmission of human capital that children's educational achievement depends strongly on the educational and health level of their parents (e.g. Black et al., 2005; Choi, 2011; Haveman and Wolfe, 1995; Holmlund et al., 2011; Gertler et al., 2004). This intergenerational dependence may be due to different styles of upbringing between high and low educated parents, or ability which is usually higher among high educated individuals than among low educated individuals (Becker, 1993; Griliches and Mason, 1972; Mincer, 1958). These differences are likely to affect both deprivation in a region and educational performance of children. As these differences are unobservable and consequently omitted from the regression, an identification of the effect of deprivation is likely to be biased in simple Ordinary Least Square (OLS) regressions due to omitted variables. Furthermore, the selection of families into deprived neighbourhoods, or reversely the selection of families out of deprived regions, may bias our results as the determinant of selection is also unobservable. We can write the relationship in which we are interested in a hierarchical model as follows

$$APR_{ijt} = \alpha + \beta MDM_j + \gamma UH_{it} + \mu EW_j + \delta X_{ijt} + \epsilon_{ijt} \tag{1}$$

where i is the subscript for individual schools, j is the subscript for electoral wards, t is a subscript for years, APR is average pass rates which is the dependent variable, MDM is the multiple deprivation measure which is endogenous, UH is school unobserved heterogeneity, EW is electoral ward unobserved heterogeneity, X is a vector of exogenous regressors and comprises both school level and ward level observable characteristics, α, β

γ, μ and δ are regression coefficients and ϵ is the error term. If UH was observable, the error term would be uncorrelated with the regressors by definition. Since we cannot measure UH the OLS coefficient of MDM is inconsistent as $COV(UH_i, \epsilon_i) \neq 0$, and biased. The direction of the bias is unclear, as ability and the style of raising children are just few examples of innate characteristics or behavioural differences that may affect both deprivation and school performance in a region. We will refer the unobservability of EW below.

The usual way to deal with omitted variable bias is to instrument the endogenous variable with one or more variables which are correlated with the endogenous variable and uncorrelated with the error term (Angrist and Pischke, 2009). Therefore we estimate a reduced form equation of the endogenous variable MDM on all exogenous regressors X and an instrument z:

$$MDM_j = \alpha + \kappa X_{ijt} + \lambda z_j \eta_{ijt} \quad (2)$$

where κ is a vector of regression coefficients and η is the error term. For z to be a valid instruments it must be partially correlated with MDM, i.e. $\lambda \neq 0$, and it must be uncorrelated with the error term ϵ , i.e. $COV(z, \epsilon) = 0$ (Wooldridge, 2002). Plugging equation 2 into equation 1 and rearranging, we obtain a reduced form equation for APR of the form:

$$APR_{ijt} = \alpha + \rho X_{ijt} + \zeta z_j + \nu_{ijt} \quad (3)$$

where $\nu_{ijt} = \epsilon_{ijt} + \beta \eta_{ijt}$, $\rho = \delta + \beta\kappa$ and $\zeta = \beta\lambda$. Assuming that ν is uncorrelated with the regressors in equation 3, the reduced from parameters are consistently estimated in the two-stage least squares model (2SLS) (Wooldridge, 2002).

We chose as instrument a variable which measures the spatial difference in intensity of violence. This measure is the total number of deaths by electoral ward between 1969 and 1994 taken from Sutton (1994) as explained in Section 4. We assume (and show) that previous regional conflict intensity is highly correlated with regional deprivation between 1999 and 2010. It may be the case that conflict intensity was higher in already deprived regions, i.e. there may be reverse causality, but we argue that regional conflict intensity has at least increased regional deprivation. It has been shown that with increasing conflict intensity house prices were reduced as people moved to less violent neighbourhoods (Besley and Mueller, 2012). Of course, not all families moved to less violent areas and presumably those families with more financial means moved away. This selection based on financial means is likely to have led to deprivation of such areas. As deprivation is measured by several domains which are by definition correlated with financial or economic status we see a clear causal effect, even if it is just a worsening rather than an activating effect. In fact, violence occurred mainly during the 1970s, 1980s and first half the 1990s and we observe deprivation from 1999 onwards. We believe that using violence intensity is a valid instrument because the multiple deprivation measure comprises many domains which could be affected by violence but which at the same time should capture any direct effect that previous violence intensity could have on school performance several years later.

We suspect that in the relationship that we are estimating, unobserved heterogeneity which varies by time and region but not by individual schools, and which is uncorrelated with the regressors, may also be present. EW_j represents this 'random effect' in equation 1. To prevent the potential bias in our estimated coefficients, we estimate a random effects two-stage least squares model (RE2SLS). This model is explained in (Balestra and Varadharajan-Krishnakumar, 1987). It allows for a more general error structure than is required for consistency in the 2SLS estimation. Clarke et al. (2010) discuss the usefulness of estimating random effects models in education research. Although their smallest unit of observation are pupils and the second level of analysis are schools, the modelling strategy can easily be 'up-scaled' in the sense that our unit of observation are schools and the second level are electoral wards. They state that, apart from the strong and often unrealistic assumption of independence between the 'random (second level of analysis) effects' and the other regressors, the random effects approach is preferable over the fixed effects approach because (1) it is able to estimate coefficients of time-invariant regressors, (2) it has the ability to estimate shrunken residuals, (3) it is able to account for differential ward effects and (4) is more efficient. These advantages of the random effects model in hierarchical data are only valid if the selection process is well understood. In our case we use the instrumental variable approach to account for selection issues at the school district level.

Furthermore, we estimate an error component two-stage least squares model (EC2SLS) proposed by Baltagi (1981). The EC2SLS model is essentially an extension of Balestra and Varadharajan-Krishnakumar's model in the sense that it expands the set of instruments used in RE2SLS. More formally, consider the set of instruments Z, the within-transformed instruments $\widetilde{Z}$ and the between transformed instruments $\overline{Z}$. While RE2SLS used the weighted sum of the within-transformed and the between-transformed instruments, in EC2SLS both $\widetilde{Z}$ and $\overline{Z}$ are used. It is shown in Baltagi and Li (1992) that both models estimate the same asymptotic variance-covariance matrix in infinite samples. Finally, it would be desirable to estimate a fixed effects two-stage least squares model since time-invariant school-specific unobserved heterogeneity may be present. Since most of our regressors are time invariant, especially the measure of violence intensity, we are unable to use this method. Baltagi's EC2SLS is a matrix-weighted average of between RE2SLS and fixed effects 2SLS and hence is a preferred model. Baltagi (2008) provides more technical details of the models.

5 Results

To contribute to the literature on violent conflict and its consequences we will discuss the first-stage regression in detail. So far, the body of literature on violent conflict and the long-run consequences on economic outcomes is small. We provide, for the first time, evidence on the long-lasting relationship between conflict intensity and spatial differences in multiple deprivation. In the first column of Table 4 the results from the first stage are shown. The coefficient of the conflict intensity is positive and significant at the one percent level. It shows that an increase by one death in a ward increases multiple deprivation by 0.013 standard deviations. This increase is translated into a 0.06 units increase on the original MDM scale as it has a mean of 8.26 and a standard deviation of 4.89. Whilst this effects is not large in magnitude the instrument is strong enough to identify a causal effect in the second stage. The result of the weak instrument test is provided in column four (2SLS) which provides an F-statistic of 115. The first column also shows that the number of pupils per school is positively correlated with multiple deprivation and a larger pupil-teacher ratio is associated with lower MDM, holding all other variables constant. Furthermore, post-ceasefire shootings and a higher percentage of Catholics in a ward are associated with higher deprivation in an area.

Before we turn to the regression results of the second stage, we discuss the unconditional relationships between average pass rates and deaths as well as average pass rates and MDM as displayed in Figure 4. For both relationships we find a negative slope. We believe, as discussed, that violence intensity is not directly related to average pass rates, but that the legacy of the conflict is what we can see on the right side of this figure. Regional deprivation, as a result of the conflict (or intensified by the conflict), reduces average pass rates.

In fact, the conditional relation, as identified in OLS regression in column two (OLS) of Table 4 shows that an increase in MDM by 1 standard deviation is associated with a decrease in average pass rates of 3.5%. The coefficient changes only marginally when controlling for unobserved ward-time specific effects (RE). When instrumenting MDM, the coefficient doubles in magnitude. The results suggest that an increase in MDM by 1 standard deviation reduces average pass rates by 7.6%. Again, in the random effects approach, the coefficient does not change significantly. Our preferred specification is the error component two stage least squares model (EC2SLS) as it controls for both endogeneity and selection. Furthermore, the model also yields a slightly larger R^2. In

Table 4: Results

	First Stage MDM Score*	Second Stage Average Pass Rate*				
	OLS	OLS	RE	2SLS	RE2SLS	EC2SLS
No. of Deaths by Ward	0.013*	–	–	–	–	–
	(0.007)					
MDM score	–	-3.451***	-3.648***	-7.641**	-7.495***	-4.759***
		(0.378)	(0.348)	(3.720)	(2.156)	(0.733)
Number of Pupils	0.008***	-0.010	-0.035**	0.022	-0.019	-0.033**
	(0.001)	(0.024)	(0.018)	(0.035)	(0.018)	(0.014)
Ratio of Teachers to Pupils	-0.023**	0.136	0.160	0.039	0.107	0.166
	(0.009)	(0.143)	(0.131)	(0.177)	(0.118)	(0.114)
Years School Offered Gaelic	0.206	4.666**	3.723*	5.515**	4.372**	4.013**
	(0.177)	(1.936)	(2.068)	(2.201)	(1.723)	(1.675)
Percentage of Catholics	0.003**	-0.004	-0.001	0.015	0.023	0.004
	(0.002)	(0.016)	(0.014)	(0.022)	(0.019)	(0.015)
Catholic School	-0.036	0.511	0.296	0.327	0.161	0.192
	(0.059)	(0.882)	(0.668)	(0.997)	(0.641)	(0.638)
All Persons 0-15	0.001***	-0.008***	-0.005***	-0.005*	-0.004**	-0.005**
	(0.000)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
All Persons 16-39	0.001***	0.001	0.000	0.004	0.002	0.001
	(0.000)	(0.000)	(0.001)	(0.003)	(0.001)	(0.001)
All Persons 40-59/64	-0.003***	0.008**	0.004	-0.005	-0.002	0.002
	(0.000)	(0.003)	(0.003)	(0.010)	(0.004)	(0.003)
All Persons 60/65+	0.003***	-0.007	-0.005	0.007	0.005	-0.002
	(0.000)	(0.004)	(0.004)	(0.012)	(0.006)	(0.003)
Shooting Incidents by DCU	0.000	0.049	0.017	0.050	0.017	0.016
	(0.005)	(0.030)	(0.016)	(0.037)	(0.019)	(0.019)
Shooting Incidents by DCU	0.015***	-0.051	0.006	0.013	0.016	0.011
	(0.005)	(0.033)	(0.017)	(0.069)	(0.021)	(0.020)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	6226	6226	6226	6226	6226	6226
R^2	0.371	0.140		0.076		
R^2 overall			0.136		0.122	0.134
χ^2			1130		466	502
F	113	58		43		
p	0.000	0.000	0.000	.	0.000	0.000
CD Wald F				115		

Note: *Dependent variable. OLS = Ordinary Least Squares, RE = Random Effects, 2SLS = Two-Stage Least Squares, RE2SLS = Random Effects Two-Stage Least Squares, EC2SLS = Error Component Two-Stage Least Squares. CD = Cragg-Donald Wald F statistic for weak instrument identification test. Standard errors in parentheses. Standard errors are clustered at Ward level in OLS, RE and 2SLS models and based on the the GLS variance estimator in the RE2SLS and EC2SLS models. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

this model, it is shown that an increase in multiple deprivation by 1 standard deviation decreases average pass rates by 4.8%. On the unit scale of the MDM variable, this implies that an increase in MDM by one unit decreases average pass rates by 23.5%. This effect is large and alarming. Children, who live in environments which are defined by high unemployment relatively bad health amount its citizens and so on, do not do well in school. The underlying factors can be manifold. For example, parents who are ill or unemployed may not be willing or able to help children with their homework or care about healthy food which is essential for concentration. In the statistical models, the only other coefficients which are statistically significant are the number of inhabitants under the age of 16 and whether the school offered exams in Gaelic. The latter have significantly higher average pass rates than schools who offer exams only in English.

We conducted several robustness checks by altering the form of the instrument. In Table A1 we use the proxy for deaths per 1,000 inhabitants. The coefficient is not significant in the first stage but increases variation in the MDM score so that it is a sufficiently strong instrument. In the second stage, the coefficient of the MDM variable is significant in the EC2SLS model and of the same magnitude as when using the total number of death per ward as an instrument. In the following three tables we use dummy variables of conflict intensity as instruments, with the thresholds (a) at least one death per ward (Table A2, (b) at least five deaths per ward (Table A3) and (c) at least 10 death per ward (Table A4), respectively. The results from the first stage indicate that the relationship between regional differences in conflict intensity and deprivation is not linear. Only the second of the three variables is statistically significant. However, in all three models, the coefficient is positive and standard errors show that the relationship is greater than zero. In the robustness checks, we find almost identical coefficients of the MDM score in the EC2SLS models. Independent of which form of the instrument is used, the coefficient ranges between -4.3 and -4.8.

6 Conclusion

Human capital is an important driver of future labour market outcomes. The accumulation of human capital prevents living in poverty and, for adolescents, being in school reduces the chances of criminal behaviour. Often, someone who lives in poverty, i.e. living with relatively low income that is not sufficient to pursue a decent life, is prone to live in an environment where average poverty is also high. Living in such a neighbourhood has consequences for individual outcomes, as shown in the neighbourhood effects literature (e.g. Weinhardt, 2010; Oreopolous, 2003; Jacob, 2004; Durlauf, 1996; Gibbons, 2002; Bauer et al., 2011).

It is not well understood though, how neighbourhood effects are best defined and how to identify causal effects. We use, as suggested by Gibbons (2002), a deprivation measure which includes several domains of deprivation: income deprivation, employment deprivation, health deprivation and disability, education, skills and training deprivation, proximity to services deprivation, living environment deprivation and crime and disorder. Using this average measure of the domains, we estimate the effect of multiple deprivation on average pass rates from primary school Key Stage II exams in Northern Ireland. Northern Ireland is an interesting case, as regional and horizontal inequalities are prevalent in this country for decades.

The history of Northern Ireland serves as an important feature which makes this study feasible. The country was hit by a long-run low intensity violent conflict, in which more than 3,500 individuals lost their lives due to terrorist attacks. Loyalists and Unionists (mainly drawn from the protestant population) and Republicans and Nationalists (mainly drawn from the catholic population) fought over unifying Ireland vs. remaining part of Great Britain. Whilst cultural identity and nationalism played important roles in the conflict, the real and perceived horizontal inequalities between the two communities are frequently cited as causes of the conflict (Fitzduff and O'Hagan, 2009). Whilst the violence largely ended almost 20 years ago, however, many of the scars of the conflict are still visible in the country.

We aim at quantifying one domain of these scars in this study, by using the spatial difference in conflict intensity to instrument multiple deprivation. This allows us to identify a causal effect of neighbourhood deprivation on school performance. Employing an error component two-stage least squares model accounts for both selection and endogeneity. We find that an increase in multiple deprivation by one standard deviation decreases average pass rates in Key Stage II exams by between 4.3 to 4.8%, depending on the form of the instrument used.

The results not only show that the violent conflict is associated with deprivation, but that has long-run indirect consequences for children, who entered school after the end of the conflict in 1994. Persisting regional inequalities in educational outcomes are an obstacle for a sustainable peace process. Policy measures have to be implemented to disentangle regional characteristics from school performance, e.g. by improving the school environment in deprived regions or reducing regional inequalities.

As horizontal inequalities are often claimed as the root of the onset of the conflict in the late 1960, it must be a policy goal to solve these inequalities. Ethnic and political differences are still not resolved, as can be reasoned by noticing the riots that are still part of modern Belfast.

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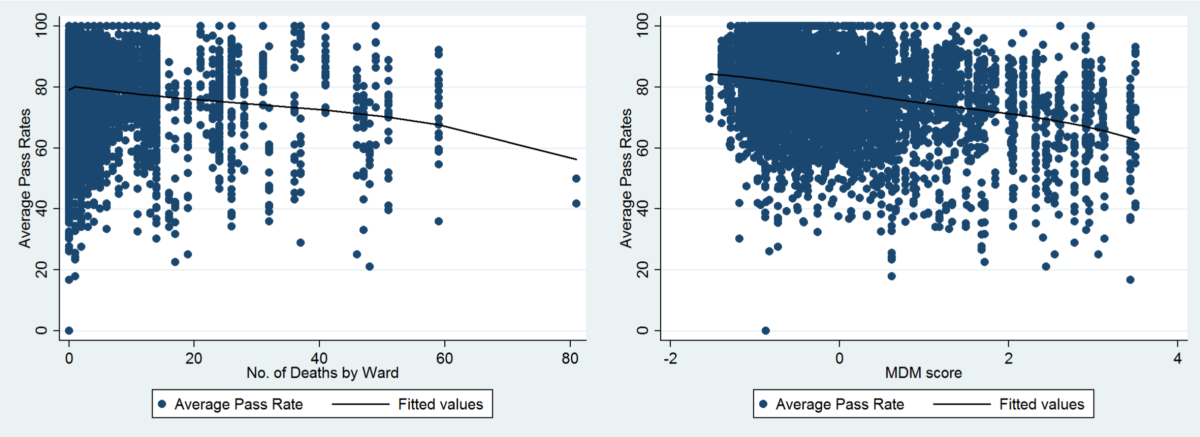
Appendix

Figure 4: Violence, MDM Scores and Average Pass Rates (Cubic Spline)



Source: Authors' construction.

Table A1: ROBUSTNESS CHECK: MDM SCORE INSTRUMENTED WITH DEATHS PER 1,000 INHABITANTS

	First Stage MDM Score*	Second Stage Average Pass Rate*		
	OLS	2SLS	RE2SLS	EC2SLS
Deaths per 1,000 inhabitants	0.031	–	–	–
	(0.022)			
MDM score	–	-6.235	-6.026**	-4.717***
		(4.497)	(2.807)	(0.710)
Number of Pupils	0.008***	0.012	-0.023	-0.031**
	(0.001)	(0.039)	(0.020)	(0.014)
Ratio of Teachers to Pupils	-0.023**	0.072	0.123	0.160
	(0.009)	(0.184)	(0.116)	(0.108)
Years School Offered Gaelic	0.206	5.230**	4.165**	4.061**
	(0.177)	(2.240)	(1.742)	(1.660)
Percentage of Catholics	0.004**	0.008	0.014	0.004
	(0.002)	(0.026)	(0.022)	(0.014)
Catholic School	-0.036	0.389	0.220	0.216
	(0.059)	(0.975)	(0.621)	(0.618)
All Persons 0-15	0.001***	-0.006*	-0.004**	-0.005***
	(0.000)	(0.003)	(0.002)	(0.002)
All Persons 16-39	0.001***	0.003	0.001	0.001
	(0.000)	(0.003)	(0.001)	(0.001)
All Persons 40-59/64	-0.003***	-0.001	0.000	0.002
	(0.000)	(0.013)	(0.005)	(0.003)
All Persons 60/65+	0.003***	0.002	0.001	-0.002
	(0.000)	(0.014)	(0.008)	(0.003)
Shooting Incidents by DCU	0.000	0.050	0.017	0.017
	(0.006)	(0.033)	(0.019)	(0.019)
Shooting Incidents by DCU	0.015***	-0.008	0.012	0.010
	(0.005)	(0.083)	(0.021)	(0.020)
Year dummies	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
N	6226	6226	6226	6226
R^2	0.367	0.112		
R^2 overall			0.129	0.134
χ^2			468	509
F	127	41		
p	0.000	.	0.000	0.000
CD Wald F		73		

Note: *Dependent variable. OLS = Ordinary Least Squares, RE = Random Effects, 2SLS = Two-Stage Least Squares, RE2SLS = Random Effects Two-Stage Least Squares, EC2SLS = Error Component Two-Stage Least Squares. CD = Cragg-Donald Wald F statistic for weak instrument identification test. Standard errors in parentheses. Standard errors are clustered at Ward level in OLS, RE and 2SLS models and based on the the GLS variance estimator in the RE2SLS and EC2SLS models. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

Table A2: Robustness Check: MDM Score Instrumented with Deaths ≥ 1 Dummy

	First Stage MDM Score*	Second Stage Average Pass Rate*		
	OLS	2SLS	RE2SLS	EC2SLS
No. of Deaths ≥ 1	0.106	–	–	–
	(0.078)			
MDM score	–	5.196	1.528	-4.334***
		(7.488)	(5.211)	(0.875)
Number of Pupils	0.008***	-0.075	-0.072***	-0.047***
	(0.001)	(0.073)	(0.027)	(0.016)
Ratio of Teachers to Pupils	-0.023**	0.337	0.252	0.202
	(0.009)	(0.217)	(0.154)	(0.142)
Years School Offered Gaelic	0.197	2.914	2.768	3.775**
	(0.180)	(2.899)	(1.894)	(1.728)
Percentage of Catholics	0.004**	-0.043	-0.034	0.001
	(0.002)	(0.042)	(0.038)	(0.018)
Catholic School	-0.045	0.892	0.238	0.103
	(0.060)	(0.865)	(0.722)	(0.714)
All Persons 0-15	0.001***	-0.015**	-0.005**	-0.004*
	(0.000)	(0.006)	(0.002)	(0.002)
All Persons 16-39	0.001***	-0.006	-0.002	0.000
	(0.000)	(0.006)	(0.002)	(0.001)
All Persons 40-59/64	-0.003***	0.034	0.008	0.002
	(0.000)	(0.024)	(0.006)	(0.003)
All Persons 60/65+	0.003***	-0.036	-0.015	-0.002
	(0.000)	(0.025)	(0.011)	(0.003)
Shooting Incidents by DCU	0.000	0.048	0.012	0.013
	(0.006)	(0.055)	(0.019)	(0.018)
Shooting Incidents by DCU	0.015***	-0.184	0.010	0.015
	(0.005)	(0.141)	(0.020)	(0.020)
Year dummies	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
N	6226	6226	6226	6226
R^2	0.362	-0.132		
R^2 overall			0.033	0.133
χ^2			437	470
F	111	55		
p	0.000	.	0.000	0.000
CD Wald F		24		

Note: *Dependent variable. OLS = Ordinary Least Squares, RE = Random Effects, 2SLS = Two-Stage Least Squares, RE2SLS = Random Effects Two-Stage Least Squares, EC2SLS = Error Component Two-Stage Least Squares. CD = Cragg-Donald Wald F statistic for weak instrument identification test. Standard errors in parentheses. Standard errors are clustered at Ward level in OLS, RE and 2SLS models and based on the the GLS variance estimator in the RE2SLS and EC2SLS models. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

Table A3: Robustness Check: MDM Score Instrumented with Deaths $\geq$ 5 Dummy

	First Stage MDM Score*	Second Stage Average Pass Rate*		
	OLS	2SLS	RE2SLS	EC2SLS
No. of Deaths $\geq$ 5	0.174*	–	–	–
	(0.096)			
MDM score	–	-1.659	-3.013	-4.610***
		(3.935)	(3.012)	(0.714)
Number of Pupils	0.008***	-0.023	-0.040*	-0.031**
	(0.001)	(0.041)	(0.021)	(0.014)
Ratio of Teachers to Pupils	-0.023**	0.178	0.173	0.161
	(0.009)	(0.144)	(0.117)	(0.107)
Years School Offered Gaelic	0.216	4.303**	3.580**	4.055**
	(0.180)	(2.121)	(1.749)	(1.658)
Percentage of Catholics	0.004**	-0.012	-0.004	0.003
	(0.002)	(0.026)	(0.023)	(0.014)
Catholic School	-0.039	0.590	0.304	0.221
	(0.060)	(0.818)	(0.617)	(0.616)
All Persons 0-15	0.001***	-0.009***	-0.005***	-0.005***
	(0.000)	(0.003)	(0.002)	(0.002)
All Persons 16-39	0.001***	-0.001	-0.000	0.001
	(0.000)	(0.003)	(0.002)	(0.001)
All Persons 40-59/64	-0.003***	0.013	0.005	0.002
	(0.000)	(0.011)	(0.005)	(0.003)
All Persons 60/65+	0.003***	-0.013	-0.006	-0.002
	(0.000)	(0.011)	(0.008)	(0.003)
Shooting Incidents by DCU	0.000	0.049	0.016	0.017
	(0.005)	(0.030)	(0.019)	(0.019)
Shooting Incidents by DCU	0.015***	-0.079	0.005	0.009
	(0.005)	(0.079)	(0.021)	(0.020)
Year dummies	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
N	6226	6226	6226	6226
R^2	0.364	0.128		
R^2 overall			0.135	0.135
χ^2			468	508
F	122	51		
p	0.000	.	0.000	0.000
CD Wald F		49		

Note: *Dependent variable. OLS = Ordinary Least Squares, RE = Random Effects, 2SLS = Two-Stage Least Squares, RE2SLS = Random Effects Two-Stage Least Squares, EC2SLS = Error Component Two-Stage Least Squares. CD = Cragg-Donald Wald F statistic for weak instrument identification test. Standard errors in parentheses. Standard errors are clustered at Ward level in OLS, RE and 2SLS models and based on the the GLS variance estimator in the RE2SLS and EC2SLS models. *,** and *** denote significance level of 10%, 5% and 1%, respectively.

Table A4: Robustness Check: MDM Score Instrumented with Deaths $\geq$ 10 Dummy

	First Stage MDM Score*	Second Stage Average Pass Rate*		
	OLS	2SLS	RE2SLS	EC2SLS
No. of Deaths $\geq$ 10	0.252	–	–	–
	(0.153)			
MDM score	–	-9.314*	-8.142***	-4.673***
		(5.551)	(2.687)	(0.749)
Number of Pupils	0.008***	0.035	-0.016	-0.035**
	(0.001)	(0.043)	(0.020)	(0.014)
Ratio of Teachers to Pupils	-0.023**	-0.000	0.098	0.171
	(0.009)	(0.210)	(0.122)	(0.116)
Years School Offered Gaelic	0.206	5.854**	4.473**	3.993**
	(0.179)	(2.440)	(1.754)	(1.678)
Percentage of Catholics	0.004**	0.022	0.028	0.005
	(0.002)	(0.025)	(0.022)	(0.014)
Catholic School	-0.042	0.253	0.141	–
	(0.060)	(1.090)	(0.648)	
All Persons 0-15	0.001***	-0.004	-0.004*	-0.005**
	(0.000)	(0.004)	(0.002)	(0.002)
All Persons 16-39	0.001***	0.005	0.002	0.001
	(0.000)	(0.004)	(0.001)	(0.001)
All Persons 40-59/64	-0.003***	-0.011	-0.003	0.002
	(0.000)	(0.017)	(0.005)	(0.003)
All Persons 60/65+	0.003***	0.012	0.007	-0.002
	(0.000)	(0.018)	(0.007)	(0.003)
Shooting Incidents by DCU	0.000	0.050	0.017	0.016
	(0.005)	(0.044)	(0.019)	(0.019)
Shooting Incidents by DCU	0.015***	0.039	0.017	0.011
	(0.005)	(0.083)	(0.021)	(0.020)
Year dummies	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
N	6226	6226	6226	6226
R^2	0.366	0.015		
R^2 overall			0.120	0.134
χ^2			459	497
F	122	44		
p	0.000	.	0.000	0.000
CD Wald F		69		

Note: *Dependent variable. OLS = Ordinary Least Squares, RE = Random Effects, 2SLS = Two-Stage Least Squares, RE2SLS = Random Effects Two-Stage Least Squares, EC2SLS = Error Component Two-Stage Least Squares. CD = Cragg-Donald Wald F statistic for weak instrument identification test. Standard errors in parentheses. Standard errors are clustered at Ward level in OLS, RE and 2SLS models and based on the the GLS variance estimator in the RE2SLS and EC2SLS models. *,** and *** denote significance level of 10%, 5% and 1%, respectively.