Growth and Violence: Argument for a Per Capita Measure of Civil War *

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Abstract

The economics literature typically uses counts of casualties as a measure of conflict intensity despite the fact that the units of observation vary considerably in population size. This article argues that this standard model is a mis-specification in the context of the economic impact of violent conflict. By adopting absolute counts the literature implicitly assumes that mechanisms at the country or state level are the main drivers of economic growth. This is inconsistent with identification strategies used in within-country studies. A per capita model of conflict intensity can bridge this gap. This article shows, using both aggregate and disaggregated data on fatalities and GDP, that there is considerable support for the per capita model in the data. The share of the population that is affected by conflict locally is a crucial variable for understanding the macroeconomic effects of conflict.

Keywords: civil war, conflict, growth

JEL-Codes: D74, O11, O47

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1 Introduction

The empirical study of civil war has recently experienced a boom. An important tool for this research has been data on conflict victims both at the country level and, more recently, within countries. Typically, empirical work uses the absolute number of victims or conflict events to distinguish between different intensities of violence.[1] The UCDP/PRIO Armed Conflict Dataset, for example, offers two thresholds of 25 and 1000 battle related deaths to define dummy variables which have been used extensively in the between-country literature. Even when other data is used, counts of deaths are an important element of the way civil wars are defined. Yet, countries differ significantly in their population size. Absolute counts are therefore applied to units of observation that are extremely heterogenous. Perhaps as a consequence, there is a strong positive correlation between population size and the prevalence of civil war in the cross-section (see Figure 1).[2] Yet, the potential problems inherent in combining absolute counts with large differences in population size have remained under-researched.[3]

This article discusses the choice between absolute counts (the standard model) and counts weighted by population (the per capita model) at the example of the economic consequences of violence. We provide a model of economic growth to highlight a central identification issue linked to the choice between these two models. The standard model assumes that the effect of violence is non-depletable at the country level, i.e. it assumes that the negative effect of violence in a country is independent of the population in that country.[4]

This assumption brings between-country studies into a conflict with within-country studies which typically identify the impact of violence from differences across regions within a country. If the standard model is correct, the reliance on regional differences makes identification of the economic consequences in within-country studies impossible. There is, however, another possibility. The economic consequences of violence could be restricted to the local level which makes identification through within-country studies possible but heavily distorts the standard approach

[1] See, for example, Besley and Persson (2011), Brueckner and Ciccone (2010), Collier et al (2009), Esteban et al (2012), Faeron and Laitin (2003), Miguel et al (2004).

[2] Figure 1 shows twenty country groups in which each group contains 5 percent of the sample. Countries are grouped according to their population size and the graph reports the log of the mean within the group. The pattern for the lower threshold of 25 casualties is the same.

[3] Brückner (2010), for example, attributes the link between population size and absolute conflict measures entirely to destabilisation caused by population.

[4] This makes violence an impure public bad. We discuss this in more detail below.

in between-country studies. Our model allows us to build a bridge between these two polar opposites. In this way we open a theoretical avenue for comparing the results from between-country and within-country studies in this quickly growing literature.

We explore these issues empirically with data on growth and violence on the country and geographic grid level. We first take a between-country view and study the effect of civil war on GDP per capita growth in a country panel. We show that the standard model can be rejected at this level. Defining civil wars with the number of battle-related deaths ignores significant heterogeneity with regard to population. The economies of populous countries appear to be significantly less affected by violence than the economies of less populous countries. When we analyze the economic impact of civil wars on growth, the per capita measure produces estimates that are more than 20 percent larger than in the standard model.

To get a within-country angle on the issue we then bring the model to data from Africa which is disaggregated by 1-degree cells. We show that there is strong local relationship between violence and economic growth. Violence in a cell affects growth negatively and this relationship amplifies for more intense violence.[5] For every year that a cell experiences more than 50 fatalities growth is reduced by about 4.4 percentage points. We find some evidence for local spatial spill-overs and country-level effects but there is also evidence for a spacial decay of the effects of violence. These findings suggest that the standard model at the country level is a mis-specification. Existing between-country work probably suffers from an attenuation bias induced by the use of the standard model.

Our model and findings at suggest that local violence combined with population weights can be used to explain the between-country effects of violence. As a final step we therefore use data on local population numbers to show that the share of locally affected population in a year is a good predictor of the macroeconomic damage inflicted by violence. In addition, the magnitudes we find are quite close to our findings from the within-country level if we take into account local spillovers. If half the population of a country lives in cells with more than 50 fatalities, growth at the country level is 7.5 percentage points lower. We conclude the discussion by providing some evidence that the share of affected population also explains refugee numbers and changes in child mortality well. This confirms the role played by local disruptions in explaining the growth performance of countries in conflict. A finding that is very much in line with recent findings on

[5] The assumption of violence as a public bad appears to be justified at this level of disaggregation.

health, education and investment from within-country studies.

We proceed as follows. Section 2 discusses some of the related literature to show that the issue of scale is largely sidestepped. The following section provides the theoretical underpinnings of identification in between-country and within-country studies in the literature. In Section 4 we illustrate the importance of this issue with the analysis of the impact of violence on per capita GDP growth at the between- and within-country level. Section 5 provides a discussion of the results.

2 Related Literature

The measurement and definition of civil war has always been a contentious issue.[6] However, there is fairly large consensus regarding the use of absolute numbers, or dummy variables based on these numbers, as a measure for intensity of mass violence in the empirical literature. The theory behind using absolute numbers, the standard model, is rarely made explicit. This section aims to provide a brief overview over the literature on the economic consequences of civil war and armed conflict. In addition, we provide a brief discussion of the literature on causes of conflict as this literature faces related conceptual problems.

We start our discussion with the macro literature on the effects of violence. This literature has typically taken a country-centered approach. Countries are regarded as the correct unit of observation and GDP per capita is assumed as coming from a representative agent (see, for example, Murdoch and Sandler (2002), Cerra and Saxena (2008) and Mueller (2012)). The implicit assumption is that economic activity by the representative agent is affected by mass violence in a way that is independent of how many people she represents. One explanation of this view is that civil wars are political crisis that affect the economy through the state, i.e. different population sizes can be ignored. One of the few papers that make this explicit is Besley and Persson (2010) who explain the rise of state capacity, measured by the share of taxes in GDP per capita, through internal and external wars. Following their theoretical framework they use the standard model and find that internal wars hinder state capacity. Collier (1999) uses the standard model and finds that civil war reduces growth by 2.2 percent. This number has been

[6] See Sambanis (2004) for an excellent review. Sambanis also briefly discusses a relative threshold but for different reasons.

used extensively in policy work like The Copenhagen Consensus project and by the World Bank.[7]

Given the existing identification problems at the between-country level the literature has moved to the sub-national level and towards specific mechanisms. For example, Akresh et al (2012a,b) and Minoiu and Shemayakina (2014) study the long run effects on health. There is also considerable evidence that investment and education are hindered by violence. Besley and Mueller (2012) study the impact of (expected) violence on house prices in Northern Ireland.[8] León (2012) studies the impact of political violence on education during the 1980s and 1990s in Peru. Annan and Blattman (2010) study abducted child soldiers in Uganda through survey work and find large effects on educational outcomes from abduction. Voors et al (2012) use a series of field experiments in rural Burundi to examine the impact of exposure to conflict in the period 1993–2003. They run a series of experiments to elicit preferences in 35 randomly selected communities in 2009 and compare communities that were affected by violence with those that were not. They observe a positive correlation between community-level conflict intensity and risk seeking and an increase in discount rates. All these studies identify the impact of violence through within country variation across regional units or ethnic groups. This means that identification hinges on different behavior in the most affected parts of the population compared to other regions.

A similar conflict between within-country and between-country views exists in the literature on the causes of violence. Again, the between-country literature has predominantly used the standard model. Hegre and Sambanis (2006) explicitly state that the likelihood of civil war rises with higher population because of scale but use this argument only to argue for population as a control variable. Collier, Hoeffler and Rohner (2009) also use the standard model in combination with per capita data. Esteban, Mayoral and Ray (2012) theoretically derive a per capita conflict effort. Their paper is one of the rare examples that derives the regression equation directly from a micro-founded theory. However, they still use the standard model and control for population.[9] There is quickly growing literature that uses exogenous shocks to GDP per capita to explain civil

[7] See, for example, Collier et al (2003) or Dunne (2013). Similarly, the World Development Report 2011 uses death counts to define years with "major violence" at the country level.

[8] They assume a public bad aspect of violence at the regional level and therefore use the standard model within Northern Irish regions.

[9] It can be shown that one of their results which holds at the 25 threshold does not scale up; results are not robust to using the 1000 threshold. However, results are strikingly consistent when the per capita model is used. This is to be expected from their theory.

conflict at the country level.[10] Bazzi and Blattman (2014) provide a review of the price shock literature. They discuss existing theories that link violence and income shocks and provide a tour-de force through possible empirical specifications. They also offer an intriguing interpretation of their findings which, in line with their use of the standard model, takes a state-centred view. In this view, lasting mass violence is the effect of a weak state. Strong states are able to stop violence quickly. However, it is not clear how to combine this idea with the results in within-country studies like Dube and Vargas (2012) who find an effect of price shocks on the absolute number of killings (events) for regions in Colombia. If Dube and Vargas (2012) use the correct model then larger countries will be much more likely to cross the 25 of 1000 threshold when wages fall. It is then not correct to use the standard model at the country level if this is the main mechanism.[11]

3 A Model of Violence and Growth

As shown in the previous section the between-country literature on the economic consequences of violent conflict uses the standard model. Most within-country studies rely directly or indirectly on spatial variation of violence within countries. We now show that these two approaches identify different aspects of the impact of violence. This allows us to discuss under which conditions the standard model is identified at the between-country level. In addition, the model will allow us to make conjectures about the channels through which violence affects the economy.

3.1 Model Set-up

Assume an economy in which violence v_{ict} affects region i in country c at time t through productivity growth. Output is

$$Y_{ict} = (\Gamma_{ict} * L_{ic})^{\alpha} K_{ict}^{1-\alpha}$$

where population L_{ic} is assumed to be immobile and fixed across time while K_{ict} is assumed to be mobile. Write productivity in region i as

$$\Gamma_{ict} = \Gamma_{ict-1} e^{p_{ict}}$$

[10] See, for example, Miguel et al (2004), Bruckner and Ciccone (2010) and Hsiang et al (2011).

[11] It is also unclear how to compare their findings to the results in Berman, Felter and Shapiro (2011) who use the per capita model.

where p_{ict} is productivity growth in region i in country c at time t. Assume that this is given by

$$\begin{aligned} p_{ict} &= \kappa_c - \delta_0 v_{ict} - \delta_1 v_{ct} + \varepsilon_{ct}, \\ v_{ct} &= \sum_i v_{ict} \end{aligned}$$

where $v_{ict} \in \{0,1\}$ denotes whether a region is affected by violence and ε_{ct} is an i.i.d error term at the country level. We make the assumption that $v_{ct} = \sum_i v_{ict}$ only for simplicity. In the empirical specification we will analyze different functional forms.

The parameter δ_0 captures the local effect of violence on productivity growth. Think of this effect as the local effect of violence on worker productivity growth. Violence directly disrupts transport and production through panic and insecurity. There are various ways in which this disruption affects labor productivity growth. For example, violence inhibits education, increases depreciation of learned skills and hinders physical and mental development of children. Our model assumes that this lack of growth cannot be recovered.[12] Note that δ_0 captures a "non-rivalrous" local effect. The effect of violence on the population in each of the directly affected regions is not a function of population L_{ic}.

The parameter δ_1 captures the public bad aspect of violence at the country level. We assume that the impact of violence is "non-rivalrous" at the country level so that the number of people or regions affected does not change δ_1. There a many reasons why this might be the case. If violence in one region is related to a political crisis then it will affect productivity growth p_{ict} in other regions of the same country as well. Civil wars could imply a collapse of external trade, tourism and foreign direct investment even in those regions that are not directly affected by violence. Furthermore, the military response by the state implies that budgets are redirected towards defence and away from public services like health and education. Violence in one region can therefore harm productivity growth in other regions as well. A milder version of this public bad aspect are local spill-overs. These are present if risk perceptions, supply chains and transport networks lead to an impact of violence in one region to adjacent regions.

The model does not assume anything regarding the "excludability" of violence risk. It is, for example, possible that individuals and firms exert effort to protect themselves from violence and that this generates parts of the reduction in productivity growth.[13] The parameters δ_0 and δ_1 then capture the overall reduction growth including the effect of counter-measures.

[12] This is in line with the "forgetting by not doing" effect found in Collier and Duponchel (2013).

[13] Besely et al (2015) find such an effect in the context of Somali piracy.

We assume that productivity growth p_{ict} is observed when capital investments are made. GDP in country c is then

$$Y_{ct}^* = \left(\frac{(1-\alpha)}{r}\right)^{(1-\alpha)/\alpha} \sum_i \Gamma_{ict} * L_{ic}.$$ [14]

3.2 Identification of the Effect of Conflict

We now use this framework to analyze the impact of conflict on GDP per capita growth. Denote the share of the population that lives in regions that are affected by violence in country c at time t as

$$\lambda_{ct} \equiv \frac{\sum_i v_{ict} * L_{ic}}{\sum_i L_{ic}}.$$

Denote productivity in regions affected by violence as Γ_{ict}^v and productivity in regions not affected by violence as Γ_{ict}^{nv}. The GDP of the country can then be expressed as

$$Y_{ct}^* = \left(\frac{(1-\alpha)}{r}\right)^{(1-\alpha)/\alpha} L_{ct}\left(\lambda_{ct}\Gamma_{ict}^v + (1-\lambda_{ct})\,\Gamma_{ict}^{nv}\right).$$

We show in the appendix that for small δ_0, δ_1 and conflict duration the impact of conflict on growth at the country level can be approximated by

$$g_{ct} \approx \kappa_c - \delta_0\lambda_{ct} - \delta_1 v_{ct} + \varepsilon_{ct} \tag{1}$$

where v_{ct} is the level of violence at the country level and λ_{ct} is the share of the population directly affected by violence.

We now turn towards a theoretical analysis of between- and within-country studies in the literature when the true model is given by equation (1). At the between-country level the standard model is

$$g_{ct} = \kappa_c + \alpha v_{ct} + \varepsilon_{ct}. \tag{2}$$

This model reflects a regression of growth on a country fixed effect and a violence measure at the country level. If the true model is given by (1) then this model is specified incorrectly.

Observation 1: *Assume that equation (1) provides a correct model of the relationship between growth and violence. Between-country regressions of growth on a violence indicator v_{ct} in equation*

[14] This follows from solving for optimal capital from the first-order condition $(\Gamma_{ict} * L_{ic})\left(\frac{1-\alpha}{r}\right)^{1/\alpha} = K_{ict}^*$. This yields optimal output in region i as $Y_{ict}^* = \left(\frac{(1-\alpha)}{r}\right)^{1/\alpha}\Gamma_{ict} * L_{ic}$.

(2) then capture the impact of violence correctly only if $\delta_1 > 0$ *and* $\delta_0 = 0$*. If* $\delta_0 > 0$ *the impact of violence on growth will appear less severe if a smaller share of the population is affected.*

Observation 1 states that if violence is not a local effect on the economy ($\delta_0 > 0$) then the impact of a civil war will depend on the share of the directly affected population, λ_{ct}. Civil wars that affect a larger share of the population will be more damaging for GDP per capita growth of the country.

Typically, it is unknown which share of the population is directly affected by violence. As a first approximation of λ_{ct} in equation (1) we will use per capita violence $\frac{v_{ct}}{L_c}$ which offers a basic test of the relevance of δ_0. The introduction of $\frac{v_{ct}}{L_c}$ allows us to test whether a given level of violence v_{ct} affects countries with different population sizes differently. If local effects are important ($\delta_0 > 0$) then countries with small populations will suffer more from violence. As a second step we will try to capture λ_{ct} directly with the help of within-country data.

We now turn towards the identification strategy in within-country studies. These studies typically use a comparison between violent and non-violent regions. This approach compares outcomes like education or body size of cohorts that grew up in regions and at a time of violence and compare these outcomes to other cohorts. Assume we had a proxy of productivity, Γ_{icT}, in region i at time $T > t$. Then we can back out the effect of violence if we compare productivity in violent and non-violent regions

$$\hat{\alpha}^{micro} = \ln \Gamma_{icT}^{nv} - \ln \Gamma_{icT}^{v}$$

which, under the assumptions above is

$$\hat{\alpha}^{micro} = s\delta_0$$

where s is the length of the exposure to violence in the specific cohort. Note, however, that the true effect of violence on individuals in violent regions is $s(\delta_0 + \delta_1)$. The differencing across regions assumes that violence is not a public bad at the country level and therefore misses a part of the effect if $\delta_1 > 0$. Within-country studies capture the true local effect of violence but they miss broader effects at the country level. If broad factors, like inter-regional transport, foreign trade and investment or the breakdown of public good provision play a big role in productivity growth then spill-overs are likely.

Observation 2: *Within-country studies correctly identify the local effect of violence,* δ_0*. If violence has elements of a public bad at the country level* ($\delta_1 > 0$) *then within-country studies will provide an underestimate of the effects of violence.*

The standard model used at the country level assumes that the marginal effect of a death on per capita growth is constant across time and countries. Observations 1 and 2 together show that this misses exactly the part of the effect of violence that the within-country studies identify. If local effects are important, and there is evidence for this from within-country studies, then the impact of violence at the country level is a function of the share of the population that is affected. In the per capita model the effect of violence is assumed to fall with population. If data on the share of individuals that are affected by violence is not available, per capita violence at the country level provides a first test of the relevance of local effects.

4 Economic Growth and Violence

In the previous section we have shown that the use of the standard model in between- and within-country studies will lead to the identification of different aspects of the economic damage caused by conflict. Within-country studies identify a local effect that makes productivity growth of different regions diverge. If this is an important factor, growth at the country level is a function of the share of the population living in these regions.

We now bring these insights to the data. For this we match four datasets. First we match data on battle-related deaths from PRIO/UCDP with GDP per capita data from the Penn World Tables. This gives us yearly data from 1950 to 2011 and for 187 countries. We then study growth and violence at the within-country level for the African continent. For this we match the Geographically based Economic data (G-Econ) with spatially disaggregated data on fatalities from UCDP. This gives us data for five-year periods between 1990 to 2005 for 2749 cells. For a detailed discussion of the sources and data see the appendix.

Table 1 provides summary statistics. At the country/year level, the average number of battle deaths is 380 while growth was 2.23 percent. The population mean in the sample is 29 million while the standard deviation is over 100 million. This implies that the country level analysis will use GDP per capita growth from countries with vastly different population sizes. This is of crucial importance for the interpretation of the results. Civil wars, according to the standard definition defined as years with more than 1000 battle-related deaths, affected 5.2 percent of all country/years in our dataset.

We also present summary statistics for the cell level data from Africa in Table 1. Average growth in this sample is somewhat lower on average, 6.26 percent in five years. This reflects lower average growth on the African continent as compared to other continents. We define a dummy that captures whether a cell has seen any violence and whether it has seen violence that exceeded 50 fatalities. Table 1 shows that, on average, cells experienced 0.31 years with fatalities in five years. This implies that the average propensity of experiencing violence in a year was about 6 percent. High intensity violence of 50+ fatalities was experienced by about 2 percent of cells every year.

4.1 Heterogeneous Effects at the Country Level

We first turn towards the country data without using information from within countries. We use the standard model in equation (2) and add year fixed effects. The resulting regression equation is

$$g_{ct} = \kappa_c + \eta_t + \alpha v_{ct} + \varepsilon_{ct} \tag{3}$$

where g_{ct} is per capita GDP growth, v_{ct} is a violence measure, μ_c are country fixed effects and η_t are year fixed effects. The parameter of interest is α. We expect this to be negative if violence hinders economic activity. The identification strategy in equation (3) follows the macro literature. The assumption is that controlling for country and year fixed effects takes care of problems of omitted variable bias. Reverse causality is assumed not to be a problem. This is in line with the ambiguous effect of income on conflict found in the literature.[15]

As an alternative, we approximate the per capita model from equation (1) by running

$$g_{ct} = \kappa_c + \eta_t + \beta \frac{v_{ct}}{L_c} + \alpha_1 v_{ct} + \varepsilon_{ct}. \tag{4}$$

where L_c is the average population of the country. In order to prevent confounding time variation in population with variation in violence we use L_c instead of a time-varying measure L_{ct}. If there are no local effects of violence ($\delta_0 = 0$) we expect $\beta = 0$. However, if violence has a local effect on the economy we expect $\beta < 0$. This follows directly from the model in equation (1) which states that the impact of violence v_{ct} is less severe if the overall population of a country is larger. The interpretation of the estimated coefficient $\hat{\beta}$ in equation (4) is not straightforward as it captures both the average population size of regions and δ_0. However, the estimated coefficient $\hat{\beta}$ should provide a first impression of whether countries with a large population are affected less by violence.

[15] There are at least two relevant links between income and conflict which suggest effects could go in opposite directions. Negative income shocks could raise the likelihood of conflict as shown by Miguel et al (2004). Positive income shocks could raise the likelihood of conflict as shown by Lei and Michaels (2014). Dube and Vargas (2010) find evidence at the micro level for both these effects. Most recently, evidence hints at a relatively weak link. See, for example, Bazzi and Blattman (2014) and Sarsons (2015).

The results from estimating equations (3) and (4) are in Table 2. In column (1) we use the civil war dummy from the standard model. If we interpret the coefficient in Table 2 as causal, a civil war year as defined by the 1000 deaths threshold reduces growth by about 2.8 percentage points. In column (2) we divide the civil war dummy by population in order to check whether civil war affects growth differently depending on the size of the population. The coefficient on the per capita civil war measure reveals considerable heterogeneity of the effects of civil war depending on population. Growth in more populous countries reacts less to a conflict that exceeds 1000 battle-related casualties. In fact, heterogeneity is so large that the standard measure is insignificant now. This is direct evidence against the validity of the standard model. The coefficients imply that the average country with 29 million inhabitants would suffer a reduction of growth of 1.8 percentage points. A country with 10 million inhabitants would suffer a reduction of growth by 3 percentage points and a country with 100 million inhabitants would suffer a growth reduction of 1.4 percentage points.

Columns (3) and (4) of Table 2 repeat the test in column (2) for two different measures of conflict. In column (4) the violence measure is the number of battle-related deaths at the country level. Again, we find that larger countries are affected less by violence. In column (5) we use the lower threshold of 25 battle-related deaths. Now the per capita measure is not significant but still has a negative sign.

The key point made in observation 1 is that the intensity of conflict is not captured correctly by absolute death counts if violence has a local effect. Table 2 shows that civil wars indeed affect populous countries less so that the definition of civil wars through absolute counts is a mis-specification.[16] The use of absolute counts could then lead to measurement error and attenuation bias.[17] This is important for policy analysis which typically refers to point estimates coming from the standard model.

However, there is an important caveat at this level of the analysis. More intense violence does not necessarily capture the fraction of population affected, since this depends on the spatial

[16] An alternative way to understand this mis-specification is to saturate the model with a polynomial of absolute violence counts v_{ct} and see whether any pattern in per capita terms remains. We show in the appendix that this also reveals large levels of heterogeneity by violence per capita.

[17] Indeed, appendix Table A1 shows that the point estimate of the impact of civil war increases if civil war is defined in relative terms. The per capita model shown in the table uses a dummy that has the same number of 0s and 1s but applies a constant threshold to battle-related deaths per capita instead of 1000 battle-related deaths.

location of violence and population. For example, if all of the violence occurs in one region that has a relatively small portion of the population the two measures may diverge.[18] What is needed to resolve this issue is within-country data which we move to next.

4.2 Growth and Violence at the Cell Level

We now turn towards the cell level data. The G-Econ project provides GDP data for the years 1990, 1995, 2000 and 2005 by 1 degree cells. This means we can construct growth numbers for three periods and 100km $\times$ 100km cells. We match this with data on violence from UCDP GED. This data is currently only completed for the African continent which gives us 8149 observations in 2749 cells. The average African country consists of about 130 cells. In what follows we use the standard model at the cell level. This assumes that violence is a public bad within the 100 km^2 cell.[19] As before we use a standard growth framework but now include 2749 cell fixed effects. We also use Conley Spatial HAC standard errors to control for the fact that violence clusters spatially.

Our analysis here relies on two violence codings. We code whether a cell experienced violence in a year with a dummy and sum over the number of years for the respective period, 1991-1995, 1996-2000 and 2001-2005. To capture high intensity violence we also construct a count for years in which a cell experienced more than 50 fatalities. We use this threshold as it is close to the equivalent of a civil war with 1000 fatalities for the average "size" of a civil war of 16 cells.[20] The spatial distribution of both these codings are displayed in Figures 2a and 2b. Quite clearly, many cells on the African continent experienced some violence in the period 1991-2005. Cell years with more than 50 fatalities were rarer. Violence was generally more common around the equator.

Regression results are in Table 3. We first simply analyze the effect of violent years at the cell level. We interpret the estimated coefficient as before - the effect of violence on yearly growth. In column (1) we find that violence reduces growth by about 2 percentage points. In column (2) we use the count of years that a cell has experienced more than 50 fatalities. The size of the coefficient increases to about 4.4 percentage points. Column (3) combines both counts. The

[18] We discuss this issue formally in the appendix.

[19] Table A2 shows that this assumption holds up to the test we conducted at the country level.

[20] See Figure A3 for a distribution of the size in cells of civil wars with more than 1000 fatalities. The exact cut-off does not matter qualitatively for any the results we present. Cut-offs of 25 and 100 fatalities, for example, yield the same results. Results available from the author on request.

coefficient on the violence count now captures the number of years in which the cell experienced between 1 and 50 fatalities. The coefficient is still negative but much smaller and not significant any more. The coefficient for years with more than 50 fatalities indicates a loss of growth of 3.7 percentage points and is still significant. Together this suggests that more intense violence has a larger impact on growth at the cell level.

In column (4) we add the number of violent years in adjacent cells. Again the coefficient on the number of years with local violence falls but stays significant this time. This suggests that the result in column (1) was partially driven by omitted variable bias in which spatial correlation of violence drove up the within-cell coefficient. We also find that violence in neighbouring cells affects the economy in a cell. The results in column (4) imply that if a cell experiences violence and is at the centre of 8 violent cells in a year the total effect on growth would be a reduction of yearly growth of almost 5 percentage points. Note, however, that column (4) also provides evidence for spatial decay of the effect of violence. Violence in an adjacent cell is about half as bad for growth as violence within the same cell. In column (5) we control for the total number of cell years at the country level. We find a negative but insignificant coefficient.

Columns (6) and (7) run the same analysis for cell years with 50+ fatalities. We find the same pattern as before only now results are estimated with different precision. Again, we find evidence for spacial decay. The results in column (7) imply that if two adjacent cells are affected by 50+ fatalities, both will experience a reduction of growth by over 3 percentage points, all other surrounding cells by 1.5 percentage points and all other cells in the same country by 0.26 percentage points.

Overall our cell-level analysis suggests that there are strong local negative effects of violence on growth. We find that higher intensity of violence both in terms of its dispersion and local intensity is particularly bad for economic development. The fact that we find spatial decay suggests that local effects are important. This confirms our results from the previous section. The finding that all other cells in the same country might be affected is particularly relevant in light of the theoretical discussion. It suggests that there might be negative growth effects coming through the country level. These effects can only be captured by studies that combine within-country data from several countries.

4.3 Within- to Between-Country of Violence and Growth

The within-country data provided by G-Econ and UCDP allows us to construct a direct measure of the share of the population that is locally affected by violence, λ_{ct}. We do this as follows. First we record the average population for each cell from G-Econ. We then calculate what share of the total population of the respective country lives in each cell. Finally we calculate

$$\lambda_{ct} = \frac{\sum_i v_{ict} * L_{ic}}{\sum_i L_{ic}}$$

by adding across all cells in a country. As before, we use our two definitions of v_{ict}; whether the cell has experienced any violence and whether the cell has experienced 50+ fatalities.

We use the first definition to compare our measure of λ_{ct} to the total number of cells that are affected by violence, $\sum_i v_{ict}$. This comparison allows us to differentiate between a measure using population weights from a measure which is closer to the standard model. Figure 3 shows that there is a considerable amount of heterogeneity across countries. In some countries up to 45 cells are affected in a single year but this represents less than 20 percent of their population. In the other extreme more than 60 percent of the population is affected but fewer than 10 cells. If we use the count of cells, larger, more populous countries will tend to be more affected by violence, and if we use the share of affected population they will tend to be less affected.[21]

In Table 4 we show the relationship between growth and our measure of violence intensity λ_{ct}. Column (1) shows the results if we count any violence at the cell level. The coefficient suggests that if half the population lives in cells with violence, growth in the country is 3.5 percentage points lower. As before, violence of higher intensity seems to do more damage. The coefficient in column (2) suggests that if half the population lives in cells with 50+ fatalities, growth is 7.5 percentage points lower. In column (3) of Table 4 we show, controlling for the share of the population in cells with more than 50 fatalities, the share of population in cells with violence does not coincide with additional damage to growth. For this reason we focus on the higher threshold in what follows.

Table 4, column (4) shows a horse-race between a simple dummy for whether a country experienced any fatalities and our measure of λ_{ct}. Controlling for λ_{ct} the dummy capturing any violence is not significant and has a positive sign. This substantiates the idea that local effects are crucial for understanding the economic damage caused by violence. In column (5) we contrast the measure $\sum_i v_{ict}$ with our measure λ_{ct}. Again, most of the explanatory power comes from λ_{ct} which is consistent with the idea that the size of the locally affected population plays an

[21] For example, take countries with more or less than 10 million population. The number of affected cells ($\sum_i v_{ict}$) increases from about 5 in less populous countries to over 10 for the populous countries. The share of the affected population (λ_{ct}) falls from 35 percent to 22 percent.

important role in explaining the economic effects of violence.[22]

How does the magnitude of our estimates compare to our results at the within-country level? Take the results in column (6) of Table 3 and assume that a country suffers from 50+ fatalities in half its cells. The most affected part of the country, with eight affected adjacent cells, would experience a growth loss of more than 13 percentage points. The other half of the cells in the country would either not be affected at all or only indirectly affected. The resulting average could therefore be fairly close to the 7.5 percentage points implied by our results from column (2) in Table 4. This implies that country level variables are a fairly good way to capture local effects and their spillovers together.[23] If we use the specification without spillovers at the micro level the aggregate numbers become smaller, i.e. closer to 2 percentage points.

The idea in our growth model is that labor productivity growth is inhibited locally by violence. One possible channel for this link is the humanitarian crisis that is often triggered by mass violence. In order to support this idea we bring our measure λ_{ct} to data on refugees, life expectation and mortality.[24] Results are reported in Table 5. Column (1) shows the impact of λ_{ct} on refugee stocks per capita. The effect we find is statistically significant and quite large. We find that about 11 percent of the affected population leaves the country as refugees. Given that these are only refugees who leave the country this is an underestimate of the share of the population that leaves home. It should be obvious that this flight from home makes the affected population vulnerable to shortages in food, sanitation and medical supplies. Accordingly, we find large and significant effects for both infant and child mortality. Infant mortality increases by over 20 deaths per 1000 life births in the affected population and child mortality increases by almost 43 children out of 1000 births. In both cases this is close to one standard deviation. These effects are much larger than predicted by pure income effect.[25] The coefficient on life expectancy in column (5) is negative and large in magnitude but not statistically significant.[26] It should

[22] Measures based on dummies explain growth relatively well compared to fatality counts even when the latter are interacted with population weights. The only exception is the Rwandan genocide which is an outlier both in terms of the number of fatalities and growth.

[23] This conclusion holds for other cut-offs as well. Results available on request.

[24] Data sources are discussed in the appendix.

[25] OHare et al (2013) provide a meta-study of the relationship between income and mortality. They find an income elasticity of around -1. Average mortality in our sample was 75 per 1000 population. A fall in income of 15 percent would therefore lead to an increase of mortality of about 11 per 1000.

[26] A possible explanation is an increase in age for those who survive childhood. Indeed, many African countries underwent a transformation of life expectancy in this period. If we control for region/time fixed effects all results

be clear from these numbers that there could be a direct link between the humanitarian crisis and violence. The sheer size of the effect we find suggests that this could indeed be one of the mechanisms by which violence affects productivity growth.

In order to simplify the theoretical analysis we used an approximation that disregarded the fact that GDP per capita differs across regions. In line with this assumption we did not explore the rise of regional inequality that is caused by violence. To get a sense of the involved magnitudes assume again that one half a country is affected by 50+ fatalities while the other half is free of violence. For simplicity assume that there are no spillovers so that one half of the country grows, for example, by 2 percent per year while the other half shrinks by 2.3 percent.[27] If both regions start out with the same GDP the violent half of the country will produce less than 40 percent of total output at the end of a 10 year conflict. If regional inequality is in itself a cause of conflict then the local economic effects of violence could be part of a vicious cycle of poverty and violence.

5 Concluding Comments

The economics literature typically uses counts of casualties or events as the measure of conflict intensity. We have argued that with regional units that are heterogenous in population this use of absolute counts imposes a particular model which should be made explicit and, perhaps, questioned. In order to show this we distinguish between effects on the local economy and effects at the country level. By adopting absolute counts the macro literature has implicitly assumed that channels at the country or state level are the main drivers of growth. Most micro studies identify local effects and are therefore inconsistent with this view.

We suggest an alternative model that we call the per capita model. In this model casualties are weighted by population to give a measure of violence risk. Empirically we find ample support for this model, both in the cross-country data and using data on GDP within 100 km^2 cells. There seems to be a strong local component to the effect of violence. A corollary of this finding is that the share of population in a country that is most directly affected by violence should be used to explain growth at the country level. We also confirm this using a combination of between- and within-country data.

These results send a clear message. Policy-makers and researchers who want to compare the

in Table 5 are statistically significant.

[27] The difference between the two numbers comes from column (2) of Table 3.

exposure to violence in the population between countries should use the per capita measure of violence. Tracking counts of fatalities in large countries like India will lead to a wrong perception of what the average Indian experiences in a year when compared to counts in less populous countries. Existing between-country work probably suffers from an attenuation bias induced by the use of the standard model.

The per capita model could also be useful in the analysis of the causes of civil war. A central theoretical idea in this area is that conflict increases if the opportunity cost of conflict at the individual level decreases. If income from agriculture falls in a drought, for example, then violence increases because opportunities of non-violent activities decrease. This mechanism works at the individual, i.e. local level. Shocks to per capita income should therefore lead to an increase in per capita violence. If 10 million individuals lose their livelihoods in a drought then this should, ceteris paribus, lead to more fatalities than if 10,000 individuals lose their livelihoods. [28]

Local effects seem to be an important driver of the economic costs of conflict. However, the channels through which violence affects the economy are still not well understood. The way in which violence affects labour supply, investment and firm behavior are therefore promising alleys for future research. A part of this agenda is the analysis of risk perceptions during conflict. They determine how far the effect of violence reaches, to what degree it is non-depletable and how this can be reduced through policy.

[28] However, it could also be that income shocks trigger violence because they lead to a government crisis - not because they lower the opportunity costs of violence. This interpretation would be in line with findings in Bazzi and Blattmann (2014), for example.

APPENDIX

A Derivation of Effect of Violence at the Country Level

Assume that Γ_{ct-1} is the productivity in all regions in $t-1$ before violence breaks out. Growth with violence is then

$$\begin{aligned} g_{ct} &= \ln\left(\lambda_{ct}\Gamma^{v}_{ict} + (1-\lambda_{ct})\,\Gamma^{nv}_{ict}\right) \\ &\quad - \ln\left(\Gamma_{ct-1}\right) \end{aligned}$$

note that

$$\Gamma^{v}_{ict}/\Gamma^{nv}_{ict} = e^{-\delta_0}$$

so that

$$\begin{aligned} g_{ct} &= \ln\left(\lambda_{ct}e^{-\delta_0} + (1-\lambda_{ct})\right)\Gamma^{nv}_{ct} - \ln\left(\Gamma_{ct-1}\right) \\ &= \ln\left(\lambda_{ct}e^{-\delta_0} + (1-\lambda_{ct})\right) + \kappa_c - \delta_1 v_{ct} \\ &\approx \kappa_c - \delta_0\lambda_{ct} - \delta_1 v_{ct} + \varepsilon_{ct} \end{aligned}$$

where we have used the fact that $ln(x+1) \approx x$ for small x, i.e. that $ln(\lambda_{ct}(e^{-\delta_0}-1)+1) \approx \lambda_{ct}(e^{-\delta_0}-1)$ and $e^{-\delta_0}-1 \approx -\delta_0$.

Note that, as conflict goes on, productivity levels in violent and non-violent regions will diverge. If conflict persists a second year we will have, for example,

$$\Gamma^{v}_{ict+1}/\Gamma^{nv}_{ict+1} = e^{-2\delta_0}$$

this means with conflict duration denoted by s we need to assume small $s\delta_0$ for the approximation to work. Intuitively, the longer conflict lasts the less weight should regions in conflict get. We illustrate this in Figure A1 for the values of $\lambda_{ct} = 0.5$ and $\delta_0 = 0.05$. On the x-axis we depict duration s and on the y-axis the true average growth rate $\ln\left(\lambda_{ct}e^{-s\delta_0} + (1-\lambda_{ct})\right)/s$ and the approximation $-\delta_0\lambda_{ct}$ respectively. The true average growth rate is shown as a dashed line and is increasing with duration as affected regions get less and less weight. The approximation is a constant $-\delta_0\lambda_{ct} = -2.5\%$.

B The Per Capita Model as an Approximation

Optimally, we want to run the regression

$$g_{ct} = \kappa_c - \delta_0\lambda_{ct} - \delta_1 v_{ct} + \varepsilon_{ct}$$

where

$$\lambda_{ct} \equiv \frac{\sum_i v_{ict} L_{ic}}{\sum_i L_{ic}}.$$

Assume a division of countries in regions i with equal population such that $L_{ic} = L_{ic'}, c \neq c'$ for all i. Now if we run the regression

$$g_{ct} = \kappa_c + \hat{\alpha}_0' \frac{v_{ct}}{L_c} + \hat{\alpha}_1 v_{ct} + \varepsilon_{ct}$$

it provides an estimate of $\hat{\alpha}_0 = \delta_0 L_{ic}$ and $\hat{\alpha}_1 = \delta_1$. In other words, the estimated coefficient captures both the damage parameter δ_0 and the size of the population in the regions.

A problem arises if regions have different population sizes. If large regions are hit by violence, a larger share of the population will be directly affected by violence. If, on the other hand, less populous regions are affected by violence the economic effect of the same number of casualties will be smaller.

C Data Sources

C.1 Country Data

In our study of growth on the country level we try to build a panel of as many countries as possible that reaches as far back as possible. We use data on battle-related deaths by Lacina and Gleditsch (2005) between 1946 and 1989. This data is complemented by the compatible UCDP Battle-Related Deaths Dataset v.5-2013. In both of these datasets we used the "best" estimate where possible and the average between low and high when no "best" estimate was available. In order to be as consistent as possible with the casualties data we generate the civil war dummies for civil wars (1000+) and armed conflict (25+) from the data of battle-related deaths.

We merge the conflict data with the Penn World Tables data version 7.1 from Heston et al (2012). We use real per capita GDP data (rgdpl) and calculate growth as the percentage point increase of per capita GDP compared to the previous year.

The refugee data has been extracted from the UNHCR Statistical Online Population Database, United Nations High Commissioner for Refugees (UNHCR). The time period covered depends on the data availability for each country, but in most cases it goes from 1961 to 2011. Specifically, the data provides the total refugee population by origin and destination country. The category total refugees excludes several other similar groups, like: asylum-seekers (those who have applied for refugee or asylum status but have not yet received a final answer); returned refugees (those who have returned to their country of origin); internally displaced persons (IDP

– those who left their usual place of residence due to violence, armed conflict of violation of human rights, but have not crossed international borders), returned IDPs, and stateless persons. Refugees per capita is calculated using the average population from the Penn World Tables.

Life expectancy, infant and child mortality and are from the World Development Indicators Database 2012 provided by the World Bank. Life expectancy is estimated at birth and given in years. Infant and child mortality are given per 1000 life births.

C.2 Cell Data

On the cell level we use data from the G-Econ research project. This project is devoted to developing a geophysically based data set on economic activity for the world. We use the current data set (GEcon 4.0) which provides "gross cell product" for all regions for 1990, 1995, 2000, and 2005 and includes 27,500 terrestrial observations. The basic metric is the regional equivalent of gross domestic product. Gross cell product (GCP) is measured at a 1-degree longitude by 1-degree latitude resolution at a global scale. For a detailed description see Nordhaus et al (2006). We construct GDP per capita values by dividing through current population.

We match this data to data from the UCDP Geo-referenced Event Dataset which provides disaggregated conflict event data for the whole African continent. For a detailed description see Sundberg et al (2010). We use the best estimate of fatalities resulting from the event and up all fatalities in a cell. We match events to the 1 degree cells using the latitude and longitude information. As the G-Econ data provides the southwest corner we match events that are in the interval $([x...x+1], [y...y+1])$ to the G-Econ cell (x, y).

D Non-parametric Discussion of Heterogeneity

Figure A2 presents the coefficients β_i of the following regression

$$\begin{aligned} g_{ct} &= \alpha_1 v_{ct} + \alpha_2 v_{ct}^2 + \alpha_2 v_{ct}^3 + \sum_{i=1}^{10} \beta_i W_{i,ct} \\ &\quad + \gamma L_{ct} + \mu_c + \eta_t + \epsilon_{ct} \end{aligned} \tag{5}$$

where the terms v_{ct}, v_{ct}^2 and v_{ct}^3 capture violence intensity in the standard model. In order to see whether any pattern remains we add the dummies $W_{i,ct}$ which capture deciles of violence per capita, $\frac{v_{ct}}{L_{ct}}$, i.e. we group all years with violence according to their number of battle-related deaths per population and give one dummy $W_{i,ct}$ to every decile. We also control for population, country fixed effects and year fixed effects. If violence was a public bad at the country level we would expect $\beta_i = 0$ for all i or a random pattern.

Figure A2 shows a significant fall in the $\hat{\beta}_i$ after the sixth decile. Controlling for violence intensity, v_{ct}, growth is about 3 percentage points lower in years with high per capita intensity. If a larger share of the population is affected by violence the impact on the economy is worse ($\delta_1 > 0$ in equation (1)). In order to illustrate this point take, for example, violence in India in 1992 and in Nicaragua in 1978. In both episodes about 2500 persons died in armed conflict within a year. However, due to large differences in population the two observations fall into very different deciles of $\frac{v_{ct}}{L_{ct}}$. The Indian civil war episode in 1992 had an intensity $i = 2$ in equation (5) while the civil war in Nicaragua falls in the most intense violence category $i = 10$. Accordingly, there is a massive heterogeneity in what the same number of battle-related deaths meant for the macro economy in these two countries. Nicaragua's economy shrank by over 8 percent in 1978 while India's economy grew by over 2 percent in 1992.

Another fact that is revealed by Figure A2 is that the effect of violence per capita on growth is roughly linear between violence deciles and the growth effect. Violence deciles capture an exponential intensity - in each decile mean violence intensity roughly doubles. This implies that there is a log-linear relationship between violence intensity and growth. For each doubling of violence intensity the growth rate falls by a number of percentage points.

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Table 1: Summary Statistics - Cell/Cross-Country Analysis for Africa

country level, yearly data, 8642 observations

Variable	Mean	Std. Dev.	Min	Max
growth	2.23	7.04	-65	115
battle-related deaths (in thousand)	0.38	3.47	0	150
population (in thousand)	29038	107534	12	1330141
civil war (standard model)	0.052	0.222	0	1
armed conflict (standard model)	0.127	0.333	0	1
civil war (per capita model)	0.052	0.222	0	1

cell-level, 5-year periods data, 8075 observations

Variable	Mean	Std. Dev.	Min	Max
five year growth rate (in percent)	6.26	21.42	-100	284
cell years with deaths	0.31	0.88	0	5
cell years with 50+ deaths	0.11	0.49	0	5
total cell years with deaths at the country level	39.03	47.82	0	165
total cell years with 50+ deaths at the country level	12.80	19.10	0	83
population (in thousands)	277238	726899	32	22000000

country-level, 1-year periods, African continent, 1047 observations

Variable	Mean	Std. Dev.	Min	Max
growth rate (in percent)	1.405	9.131	-50.779	115.433
share of population in cells with fatalities (given fatalities>0)	0.27	0.27	0	1
share of population in cells with 50+ fatalities (given fatalities>0)	0.11	0.19	0	1
refugees per capita	0.01	0.04	0.00	0.37
life expectancy at birth	54.37	8.56	27	81
infant mortality (in 1000 life births)	73.17	31.78	6	166
child mortality under five years old (in 1000 life births)	119.77	58.33	6	288

Table 2: Heterogenous Effects of Violence at the Macro Level

	(1)	(2)	(3)	(4)
VARIABLES	growth	growth	growth	growth
civil war (standard model)	-2.818***	-1.217		
	(0.634)	(0.791)		
civil war (standard model) / population		-18,524***		
		(7,058)		
battle-related deaths			0.104*	
			(0.0599)	
battle-related deaths / population			-3.485***	
			(0.543)	
armed conflict				-1.060**
				(0.428)
armed conflict / population				-1,387
				(1,809)
country fixed effects	yes	yes	yes	yes
year fixed effects	yes	yes	yes	yes
Observations	8,642	8,642	8,642	8,642
R-squared	0.050	0.052	0.061	0.047
Number of countries	187	187	187	187

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Growth" is real GDP per capita growth in percent from the Penn World Tables version 7.1. "Civil war (standard model)" is a dummy that takes a value of 1 if the number of battle-related deaths exceeds 1000. "Battle-related deaths" are the number of battle-related deaths according to the "best" estimate from UCDP/PRIO. "Armed conflict" is a dummy that takes a value of 1 if the number of battle-related deaths exceeds 25. Population is given in 1000. Columns (2)-(4) use average population of the country within the sample period.

Table 3: Violence and Growth at the Cell Level

VARIABLES	(1) growth	(2) growth	(3) growth	(4) growth	(5) growth	(6) growth	(7) growth
number of years with fatalities	-2.121***		-0.748	-0.854***	-0.839***		
	(0.729)		(0.514)	(0.129)	(0.163)		
number of years with 50+ fatalities		-4.387**	-3.692**			-1.802*	-1.638*
		(1.714)	(1.783)			(0.943)	(0.946)
total number of cell years with fatalities in adjacent cells				-0.496**	-0.472**		
				(0.194)	(0.214)		
total number of cell years with fatalities in the country					-0.00529		
					(0.0142)		
total number of cell years with 50+ fatalities in adjacent cells						-1.470***	-1.187**
						(0.488)	(0.484)
total number of cell years with 50+ fatalities in the country							-0.130***
							(0.0363)
cell fixed effects	yes	yes	yes	yes	yes	yes	yes
year fixed effects	yes	yes	yes	yes	yes	yes	yes
Observations	8,149	8,149	8,149	8,149	8,149	8,149	8,149
R-squared	0.005	0.009	0.010	0.010	0.010	0.022	0.028
Number of cells	2,749	2,749	2,749	2,749	2,749	2,749	2,749

Conley robust standard errors in parenthesis (using 200km as correlation). *** p<0.01, ** p<0.05, * p<0.1. "growth" is the GDP per capita growth rate in percent calculated from the GECON data. "number of years with fatalities" is a count of the number of years a cell has suffered fatalities in the 5-year period. "number of years with 50+ fatalities" is the count of the number of years a cell has suffered fatalities in the 5-year period. "total number of cell years" is a count of the years in all cells in the respective sample. "adjacent cells" are the 8 cells that are within a +1 and -1 range of the latitude and longitude of the cell. The fatality data is from the UCDP geo-referenced event dataset (GED) which provides number of fatalities in each event.

Table 4: Micro to Macro Model

VARIABLES	(1) growth	(2) growth	(3) growth	(4) growth	(5) growth
share of population in cells with fatalities	-7.049***		0.335		
	(2.155)		(2.551)		
share of population in cells with 50+ fatalities		-14.90***	-15.27**	-15.59***	-13.12***
		(4.467)	(6.726)	(4.984)	(4.396)
any fatalities at the country level				0.699	
				(0.772)	
number of cells with 50+ fatalities					-0.183
					(0.161)
country fixed effects	yes	yes	yes	yes	yes
year fixed effects	yes	yes	yes	yes	yes
Observations	1,047	1,047	1,047	1,047	1,047
R-squared	0.070	0.084	0.084	0.084	0.085
Number of countryies	50	50	50	50	50

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "growth" is real GDP per capita growth in percent from the Penn World Tables version 7.1. The "share of population in cells with fatalities" and the "share of population in cells with 50+ fatalities" are calculated from the cell level using the average population in the affected cells.

Table 5: The Humanitarian Crisis as a Channel

	(1)	(2)	(3)	(4)
VARIABLES	refugees per population originating in country	infant mortality	child mortality under five years old	life expectancy at birth
share of population in cells with 50+ fatalities	0.109***	20.33**	42.77**	-7.034
	(0.0275)	(8.159)	(18.82)	(4.487)
country fixed effects	yes	yes	yes	yes
year fixed effects	yes	yes	yes	yes
Observations	1,026	672	714	1,047
R-squared	0.262	0.565	0.550	0.239
Number of countryies	49	32	34	50

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The "share of population in cells with 50+ fatalities" is calculated from the cell level using the average population in the affected cells. "infant mortality and "child mortality under five years old" are per 1000 live births. "life expectancy at birth" is given in years. Data on refugees is from the UNHCR and excludes internally displaced. Data on mortality and life expectancy is from the World Bank.

Table A1: Per Capita Civil Wars in Different Samples

	(1)	(2)	(3)	(4)	(5)	(6)
	whole sample		sample 1989-2010		poor countries	
VARIABLES	growth	growth	growth	growth	growth	growth
civil war (standard model)	-2.818***		-3.165***		-2.741***	
	(0.634)		(1.063)		(0.691)	
civil war (per capita model)		-3.540***		-4.503***		-3.720***
		(0.670)		(1.386)		(0.738)
country fixed effects	yes	yes	yes	yes	yes	yes
year fixed effects	yes	yes	yes	yes	yes	yes
Observations	8,642	8,642	3,866	3,866	4,377	4,377
R-squared	0.050	0.053	0.063	0.069	0.050	0.056
Number of countryid	187	187	187	187	93	93

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Civil war (standard model)" is a dummy that takes a value of 1 if the number of battle related deaths exceeds 1000. "Civil war (per capita model)" is a dummy that takes a value of 1 if the number of battle-related deaths per population exceeds a threshold. The threshold is chosen such that there are as many civil wars in the sample as in the standard model. Columns (1) and (2) use all data as in Table 2. Columns (3) and (4) use only data in the period 1989-2010. Columns (5) and (6) use only data from countries with GDP per capita below the median.

Table A2: No Heterogenous Effects Locally

VARIABLES	(1) growth	(2) growth	(3) growth
number of years with fatalities	-2.217***		
	(0.552)		
number of years with fatalities/population	6,987		
	(6,027)		
number of years with 50+ fatalities		-4.504***	
		(1.150)	
number of years with 50+ fatalities/population		12,305	
		(27,181)	
number of fatalities			-0.000180**
			(7.25e-05)
number of fatalities / population			-11.31
			(75.13)
cell fixed effects	yes	yes	yes
year fixed effects	yes	yes	yes
Observations	8,149	8,149	8,149
Number of cell	2,749	2,749	2,749

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "growth" is the GDP per capita growth rate in percent. "number of years with fatalities" is a count of the number of years a cell has suffered fatalities in the 5-year period. "number of years with 50+ fatalities" is the count of the number of years a cell has suffered fatalities in the 5-year period. The fatality data is from the UCDP geo-referenced event dataset (GED) which provides number of fatalities in each event. "number of years with fatalities / population" is the same number divided by the average population in the cell.

Figure 1: Population and Prevalence of Civil War

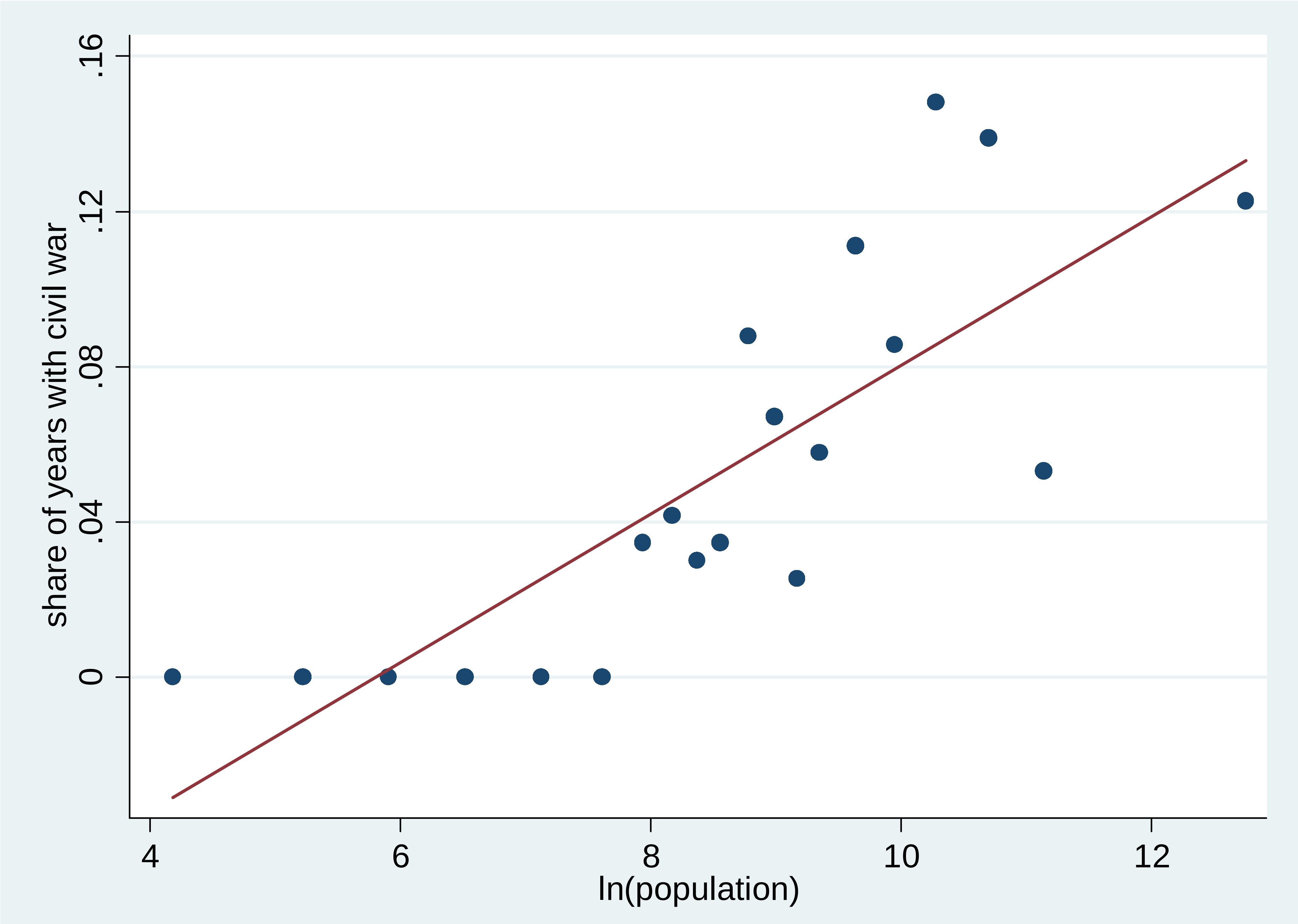


Figure 2a: UCDP GED Conflict at the G-Econ Cell Level (1991-2005)

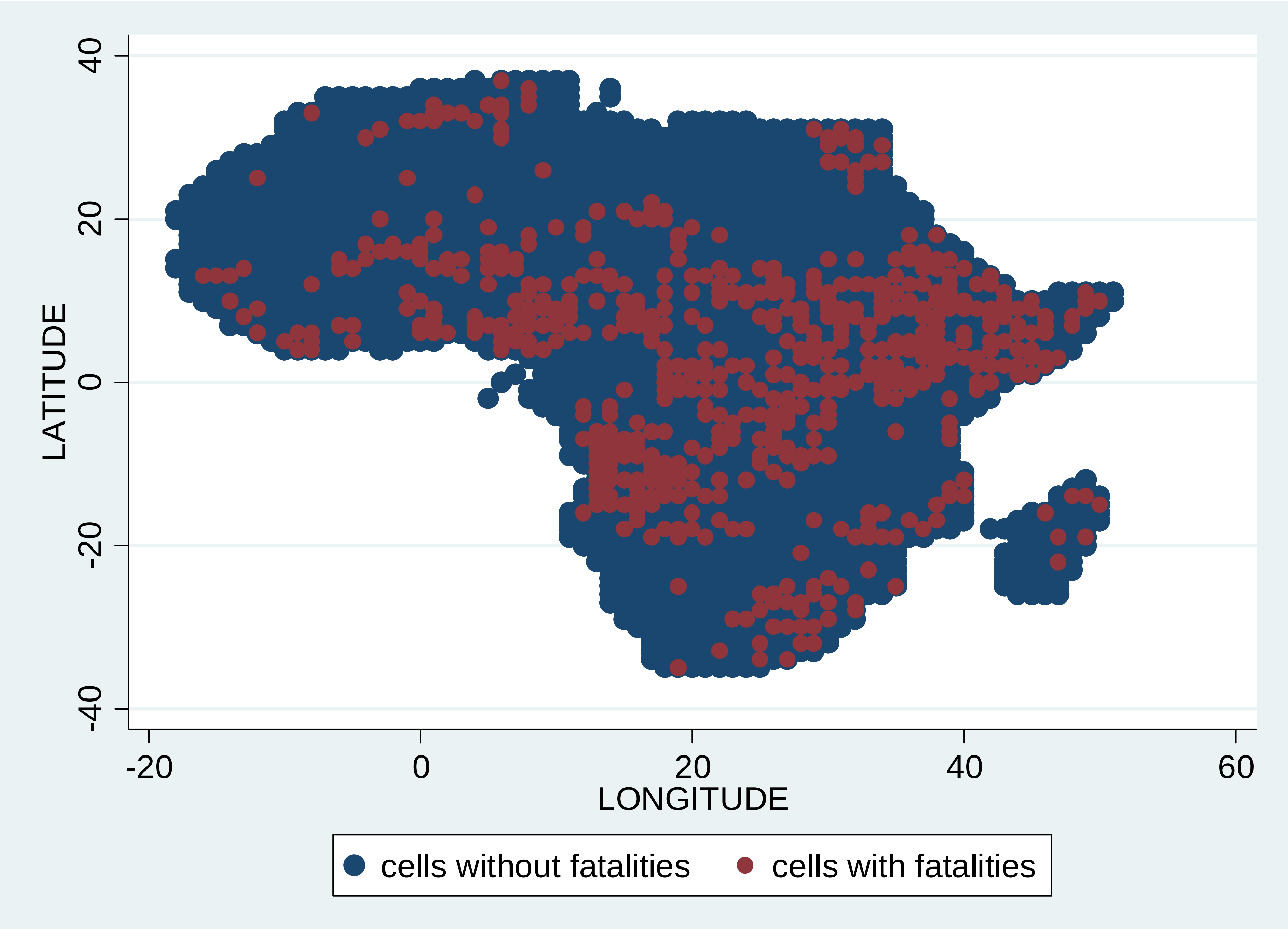


Figure 2b: UCDP GED Conflict at the G-Econ Cell Level (1991-2005)

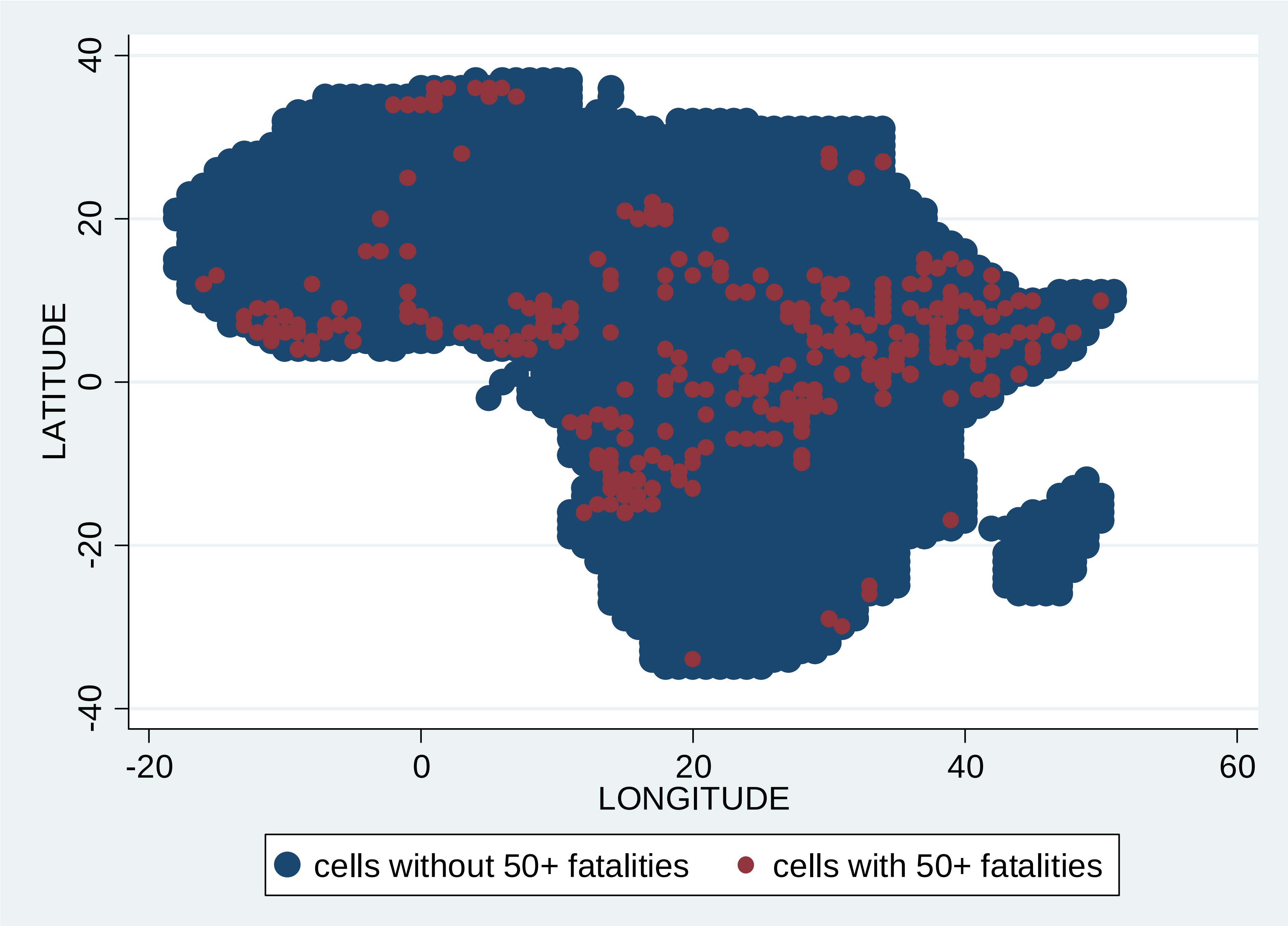


Figure 3: Number of Cells and Share of Population Affected by Violence

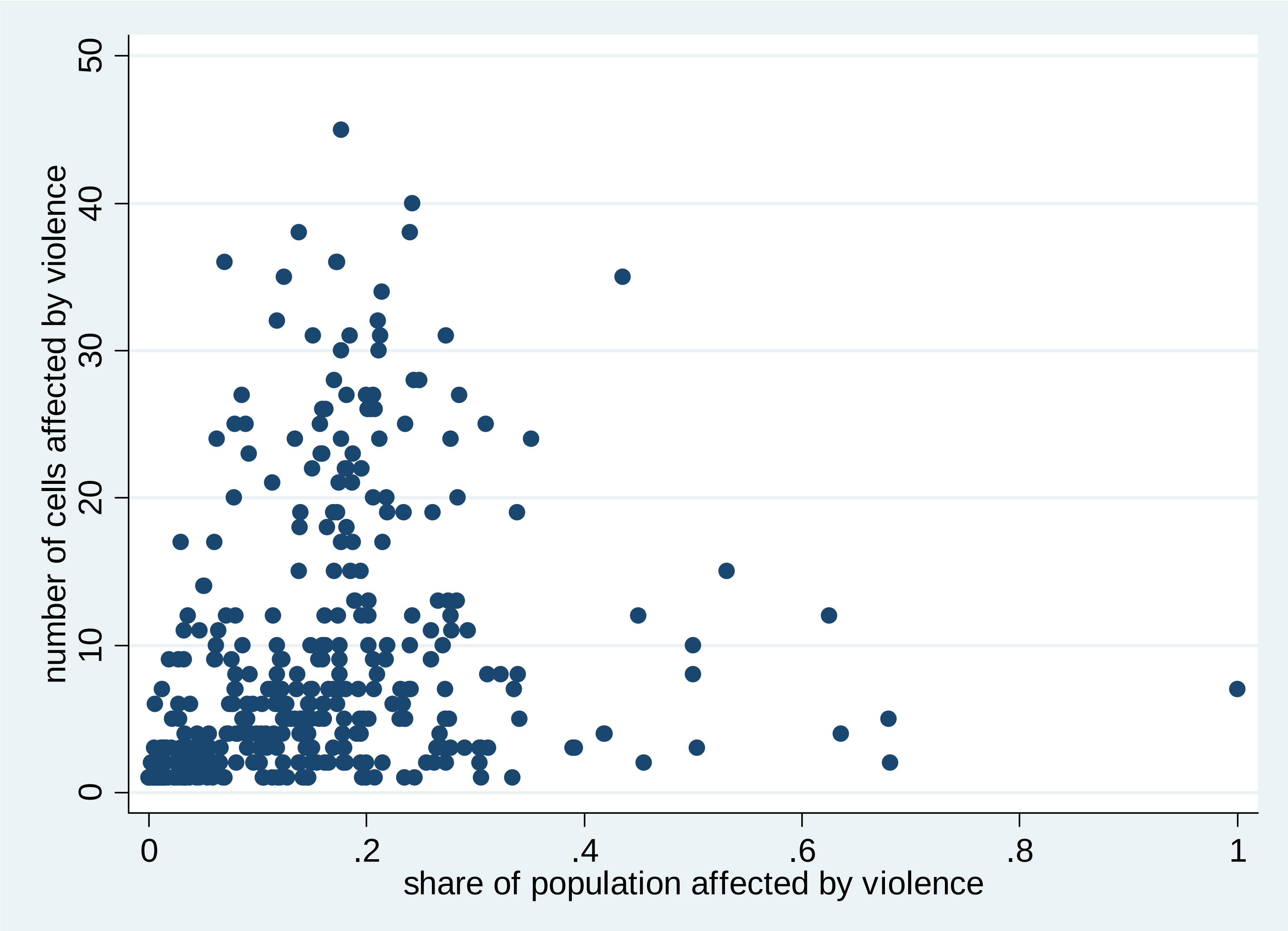


Figure A1: Approximation of Average Growth Rate (lambda=0.5, delta0=0.05)

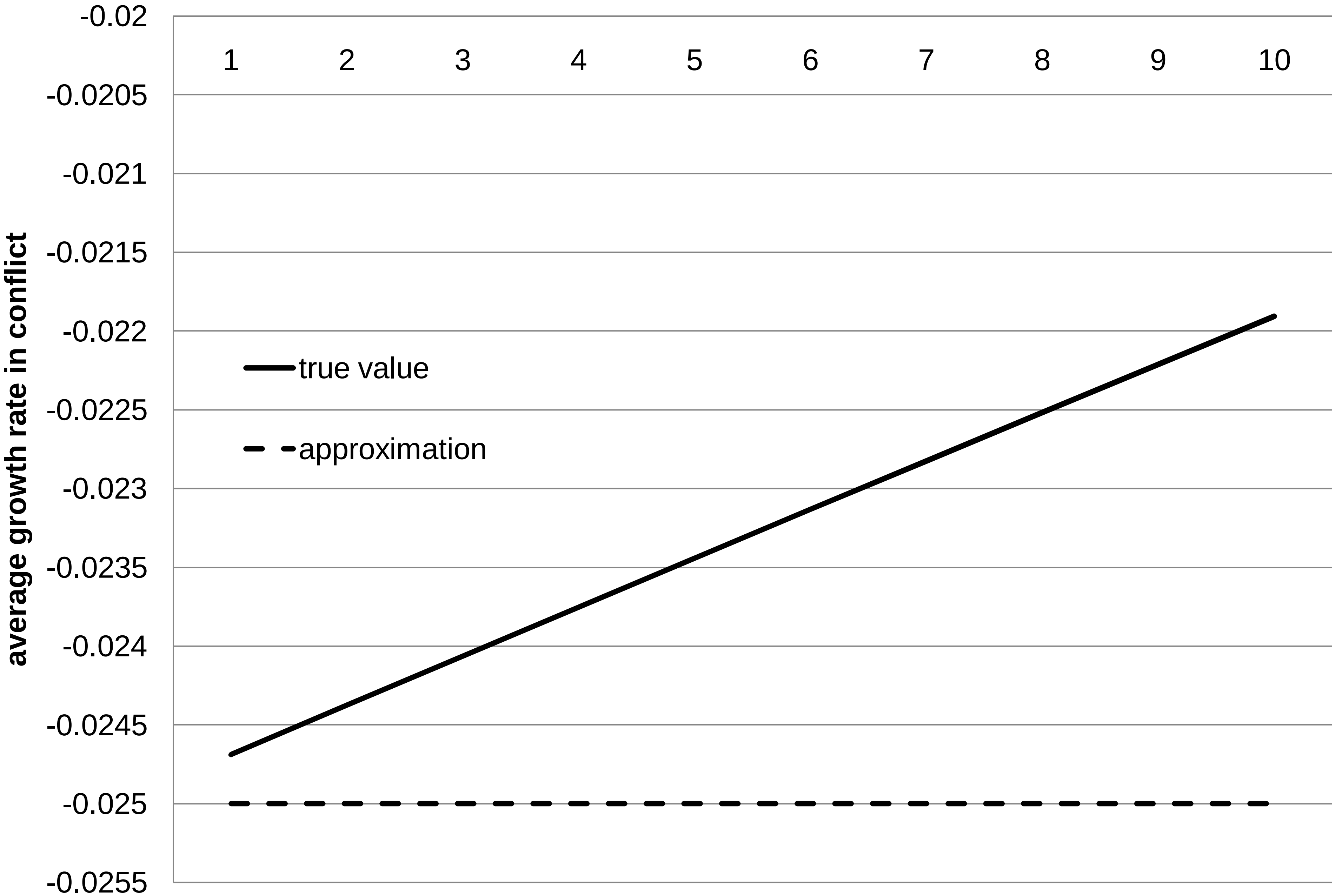
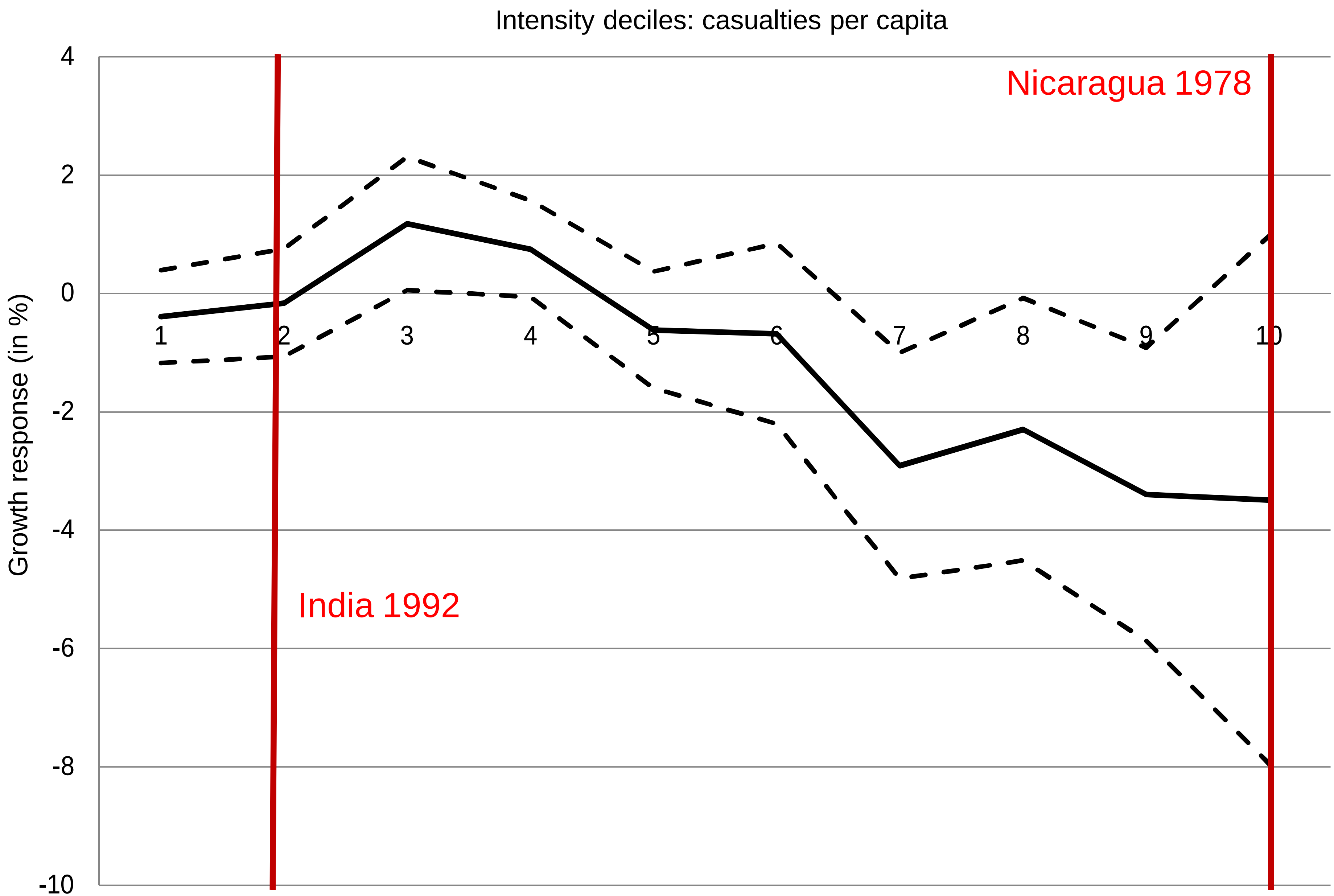


Figure A2: Violence Intensity and Growth in the Per Capita Model



Note: Solid line shows coefficients of a regression of GDP per capita growth on intensity decile dummies. The regression controls for a cube function of battle deaths. Additional controls are population, country and year fixed effects. Dotted lines indicate ten percent confidence intervals.

Figure A3: Number of Affected Cells in Country/Years with over 1000 Fatalities