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The Persistent Colombian Conflict:
Subnational Analysis of the Duration of Violence

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Abstract: The growing empirical literature on the analysis of civil war has recently included the study of conflict duration at the cross-country level. This paper presents, for the first time, a within-country analysis of the determinants of violence duration. I focus on the experience of the Colombian armed conflict. While the conflict has been active for about five decades, local violence ebbs and flows and areas experiencing continuous conflict coexist with places that have been able to resile and where violence is mostly absent. I examine a wide range of factors potentially associated with violence duration at the municipal level, including scale variables, geographical conditions, economic and social variables, institutions and state presence, inequality, government intervention, and victimization variables. I characterize a few variables robustly correlated with the persistence of localized conflict, both across specifications and using different econometric models of duration analysis.

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1 Introduction

The recent boom in the empirical analysis of civil war has produced a large body of evidence on the main correlates of conflict, its potential causes and its consequences (see for example Collier and Hoeffler, 2004; Fearon and Laitin, 2003; and Collier, 1999. Blattman and Miguel, 2010 provide a comprehensive survey of the literature). More recently, the field has started to move from the account of simple correlations to the application methodologies better suited to support causal statements, notably Abadie and Gardeazabal (2003), Miguel et al. (2004), Guidolin and La Ferrara (2007), and Dube and Vargas (2008). However, the study of the duration of violence is still in its infancy. Most of the existing empirical evidence is based on cross country analyses (Regan, 2002; Fearon, 2004; and Collier et al., 2004). While exploiting sub-national variation may be more suitable to pin down mechanisms that explain the main correlates of war dynamics, there is a sizable lack of systematic studies of the duration of violence at the within-country level.

The absence of micro-data on conflict dynamics may well explain why the literature has concentrated on macro-level correlations across countries. Important exceptions for the case of factors associated with conflict *incidence* include Deininger (2003), Barron et al. (2004), and Do and Iyer (2006), but there are no equivalent contributions for the case of conflict *duration*. Filling this vacuum is particularly relevant for policy purposes. Indeed, understanding the reasons why, in the context of nation-wide civil conflict, some regions consistently experience violence while other resile and remain relatively peaceful, and knowing what factors help inoculate communities is of first order importance for the design of policies and military endeavors.

Focusing on the experience of the Colombian armed conflict, in this paper I carry out, for the first time, a within-country analysis of the determinants of violence duration. While the Colombian conflict has been active for about five decades, local violence ebbs and flows and areas experiencing continuous conflict coexist with places where violent episodes are mostly absent. Moreover, Colombia is a good laboratory for the study of civil conflicts given the availability of a great amount of good quality micro data on the conflict dynamics.

Using survival models, I examine a wide range of factors potentially associated with violence duration at the municipal level. These include scale variables (like the size of the territory and its population), geographical characteristics (like altitude, temperature and rainfall), variables associated with state presence and the quality of institutions (police and military presence and the existence of judiciary and banks), the availability of both legal and illegal natural rents, local-level social indicators (poverty, education and infant mortality), proxies of government intervention (like aerial spraying of illegal crops and the presence of alternative development programs), inequality measures, and victimization variables. I characterize a few variables that very robustly predict whether violent episodes at the local level are likely to be long-lasting or not.

Results suggest a wide scope for public policy as violence in Colombia is less likely to be persistent in smaller municipalities, with less rents available to predate from and a more active military presence of the state. However results also point to more persistent conflict episodes in places where crop substitution programs have been implemented although this is likely to be explained by the fact that these places have had higher incidence of illegal crops in the past. Moreover, paramilitary victimization of civilians increases the hazard of conflict termination suggesting that civilian targeting has been used as a way to consolidate control by illegal armed groups (Kalyvas, 2006). This implies that seemingly "peaceful" areas are not necessarily free of illegal groups which gives further scope for government intervention. All these findings are robust to assuming different data generating processes which make different assumptions on how the underlying hazard of peace changes over time.

The remaining of the paper is organized as follows. In section 2 I give some background on the nature of the Colombian conflict, a three-sided civil war where in addition to government forces and rebel groups, paramilitary forces also fight the left-wing insurgency. Data and measurement issues are described on section 3; the statistical approach is presented on section 4 and results and robustness checks are discussed in section 5. Finally I conclude and offer some lines for future research.

2 A five-decade armed conflict in Colombia

Colombia's armed conflict involves rebel insurgencies, government forces and illegal paramilitaries.[1] Scholars identify its origin in *La Violencia,* a period of intense violence between the two traditional political parties from 1946 to 1966. Insurgent groups were formed in the early 1960s as peasant self-defense organizations originally aligned with the Liberal party. Two of them survive today as the main guerrilla organizations: the Revolutionary Armed Forces of Colombia (FARC by its Spanish acronym) with an estimated army of about 20,000 combatants that are said to include a large share of women and children, and the National Liberation Army (ELN), with a much weaker force of about 4,000 fighters. These are not the only guerrilla groups in Colombia but they are the two largest and most important. The two most important sources of finance for rebel groups from the early 1990s are the drug

[1]For a detailed account of the conflict see Rabassa and Chalk (2001).

business and the kidnapping of civilians. Drugs are a major source of finance especially for the FARC, which is known to tax coca crops, and to control the production, processing and export of cocaine and heroine. The FARC also collects 'war taxes' from other businesses and agricultural producers in their areas of operation.

The other major active armed actor of the conflict are the illegal paramilitary forces. Many paramilitary combatants have recently demobilized taking advantage of a peace process that started in 2003, but they are said to have had over 20,000 members at the peak of their strength. Paramilitaries have traditionally described themselves as self-defense groups *vis-a-vis* the advancement of the guerrillas. Without denying the existence of a self-defence component, paramilitaries are in actuality a rather complex hydra. The first paramilitaries were organized by the military during the early 1970s, following law 48 of 1968 by which president Valencia allowed the formation of self-defense civilian groups. The objective was to arm civilians for protection against insurgents. Subsequently, rural elites formed private armies which emerged on a widespread scale during the eighties when drug lords started becoming landowners and facing extortion from the guerillas. The paramilitaries were declared illegal in 1989, after which the Colombian conflict technically became three-sided. However, the vast majority of the fighting involves the guerilla against the military and paramilitary, and there are numerous allegations of collusion between the latter two groups. In 1997, disparate factions of paramilitary (including drug traffickers, disaffected former members of the armed forces and victims of the guerilla) came together under an umbrella alliance called the United Self-Defense of Colombia (AUC), which contributed substantially to the dramatic upsurge of conflict-activity during the late 1990s (Restrepo et al., 2004).

In this period, the paramilitaries acquired notoriety for their attacks against civilians. Indeed, paramilitaries are the major killers of civilians in Colombia, in 976 massacres from 1988 to 2004, they have assassinated over 6,200 civilians. Guerrilla groups, especially the FARC, have increasingly made use of this method, namely the targeting of the civilian infrastructure of the enemy to create fear and reduce the support of the other party to facilitate territorial control. However, most guerrilla events involve attacks to the infrastructure or clashes with the government, and during the same period they have carried out 197 massacres killing almost 1,200 civilians.

3 Data

3.1 Measurement issues

Previous studies of the determinants of duration of violence use cross-country variation (Regan, 2002; Fearon, 2004; Collier et al., 2004). While within-country analyses are potentially a powerful tool to understand the nature of civil war through the examination of the temporal and spatial dynamics of a conflict, war duration is conceptually not as clear at the sub-national level. From a cross-country perspective, civil war duration a is straightforward variable to code assuming the time of conflict onset and ending is known (or that it can be defined with reasonable and uniform criteria like a fatality threshold –Small and Singer, 1982). However, this definition is not directly applicable at the sub-national level since, with few exceptions like the case of India, there is usually no more than one civil conflict within a country at a specific point in time.

Thus I define the outcome variable analyzed in this paper as the duration of violence (or the duration of *violent episodes*) across sub-national units of the country. This is in turn determined by the variation in the frequency of conflict episodes across regions, which responds to region-specific incentives to control strategic territories (for either economic or political reasons) or to predate a valuable resource. To the extent that these incentives can be proxied by observable characteristics, it is then possible to carry out and empirical investigation of the determinants of the duration of violent waves across regions within a country and hence design policies to support the resilience efforts of local communities.[2]

The sub-national unit of analysis is the municipality, which is the most disaggregated political unit in Colombia and is comparable to the US county. Also, duration of violence is calculated in terms of months. Colombia has circa 1,000 municipalities and there are slightly over 1,200 civil-conflict related episodes in the country every year. That is, there are on average 0.1 conflict events per municipality-month. In fact, the more disaggregated the unit of analysis, the more rare the incidence of violence will be per unit of time. This means that it will not be a sensible choice to measure duration of violence the way it is done for cross-country analyses as one municipality is not likely to experience repeated violence month by month so to code "onset" and "end", as the first and the last months of violence.

[2]There is a large regional and temporal variation in patterns of violence in Colombia. These take the form of both uncontested attacks, generally carried out by illegal groups (like incursions, bombings, road checkpoints and massacres), and clashes against government forces. The bulk of clashes or fire exchanges in the Colombian conflict involve an illegal group (generally a guerrilla organization but in some cases right-wing paramilitaries) against government forces (military or police). However, there are some episodes of clashes between guerrillas and paramilitaries, or clashes between different organizations within the guerrilla or within the paramilitary.

For instance, imagine a municipality that has been peaceful up to December 1996. Suppose there is a guerrilla incursion in January 1997, nothing happens in February, another guerrilla incursion in March, peace in April and the guerrilla repeats the attack in May. This third time the government sends troops that find the rebels and challenge them in the battlefield, after which the municipality stops experiencing any violence. Hardly can anyone argue that there were three "violent waves" in this municipality: one in January, one in March and one on May; the three lasting one month. In contrast it makes sense to analyze this as the same, 5-month long, *violent episode.*

With this in mind I calculate the number of months between violent episodes and set an arbitrary threshold for when to count such period as violence or peace. My benchmark threshold is 12 months. This is equivalent to assume that recurrence of violence within a year of the last violent event suggests that the latent conflict has not been eradicated from the municipality, and hence we are in fact dealing with the same violence wave.[3] On the other hand, peaceful periods lasting 13 months or longer are coded as "peace" and if violence recurs after that in the same place, this is coded as a different violence episode.[4]

In Section 5 I present results using the benchmark 12-months peace threshold. However, results are generally robust to upward and downward variation of the threshold.[5]

3.2 Data

Using data from CERAC, a local think tank, I construct the dependent variable following the criteria discussed above.[6] Violence is defined as the incidence of attacks by any illegal group. There are 2,685 violence waves in the circa 1,000 municipalities of the country during the period from 1988 to 2004 (see Table 1). The average duration in months of these conflict episodes is 10 months for the whole sample. Restricting the sample to episodes that actually

[3]It is worth noting that in Colombia violence does not present a definite seasonal pattern within a given year. This does happen in other conflicts (like Afghanistan) due to the severity of the inter-season climate changes.

[4]A similar strategy is often used in the cross-country literature on the causes of war. When violence recurs shortly after the conflict ended (say, five years –Toft, 2006), the previous war is said to have *recurred* and no new war is coded.

[5]Counterparts for all the tables described in section 5, using thresholds of 3, 6 and 24 months are available by request.

[6]CERAC maintains a unique event-based dataset that covers over 21,000 conflict-related incidents over the period 1988-2004. For each event, the dataset records the date, location, type, perpetrator, and victims involved in the incident. In terms of type, it records whether the incident was an uncontested *attack,* carried out by an identified armed group against a specific military or civilian target, or a *clash*, which involves an exchange of fire between two or more groups. In terms of perpetrators, it records whether attacks were carried out by the guerilla, the paramilitary or the government, and details the groups involved in a clash. In terms of victims, it reports the number of casualties separately for combatants and civilians (see Restrpo et al., 2004 for a complete description of the CERAC dataset).

ended before the last sample-year of the dataset, that is, to uncensored episodes, the average duration is 8.1 months.

Figure 1 gives a dynamic perspective of the dependent variable by looking at the average duration of (uncensored) conflict waves that started at each single year of our sample period. After a short increase from 10 to 14 months duration in the late 1980s the average duration dropped steadily until 1995, reaching about 6 months. Conflict waves starting in 1996 jumped back up to 13 months and average duration decreased rapidly during the rest of the sample years. By 2003 conflict episodes *that had ended* (and so this is not an artifact of the right-censoring problem) were about 2 months long, indicating that by mid 2000s Colombian municipalities were experiencing much longer periods of peace.

Figure 1: Average Duration in Months of Conflict Episodes Starting in Each Sample Year

Notes. The included sample of violence waves excludes right-censored episodes. Because the complete sample period ends in 2004 and the peace threshold for coding the end of violence is 12 months the last sample year is 2003.

The conflict dataset is combined with a number of municipal-level characteristics that are potentially associated with the duration of regional conflict waves within the country and are described in Table 1. Because there is great variation in the municipalities in terms of size I include municipal-*scale* variables like the population and the area of the municipalities, which come from DANE and CEDE respectively. I also include *geographical* characteristics like average altitude, average temperature and the average amount of rainfall, which come from national agencies IDEAM and IGAC. The distance from the municipal centroid to the main markets and to the capital comes from CEDE. Variables associated with *economic conditions and the availability of rents* that can be captured by illegal groups are also taken into account. These include tax revenues and the presence of natural-resource mines (both from the National Planning Department), and the presence of coca fields (from UNODC-SIMCI). *Social variables* come from DANE include poverty (measured with a 0-100 composite index of unmet basic needs), average education of the household head both primary and secondary school enrollment, and health conditions (which I proxy using infant mortality during the first year of life). I also add *institutional and state-presence variables* like the presence of police, military bases, presence of financial institutions like banks and institutions of law enforcement like the number of judges per capita. These data con from Fundación Social (a local NGO) except for the military bases which come from the Colombia National Army. Data on *victimization* of civilians by illegal groups come from CERAC and data *government intervention* initiatives include the amount of illegal crops sprayed and the presence of crop substitution programs (both from the National Anti-narcotics Agency), as well as government attacks (CERAC). Finally *land inequality* controls like land Gini and a land polarization index are computed by me using micro-data from IGAC.

4 Empirical approach

The binary dependent variable approach often used to study the causes of war (Collier and Hoeffler, 2004; Fearon and Laitin, 2003) is not entirely appropriate when the interest is to identify the factors associated with the *duration* of violence. On the one hand, violence duration is a different question than the one on its causes, so the factors associated with each one may differ as well. On the other, the logit/probit framework does not apply when the dependent variable is not dichotomous. OLS cannot be used in this context either because it could lead to negative predicted values that do not make sense if the dependent variable is truncated at 0 as in the case of duration. In addition, a common challenge of duration analyses, that cannot be dealt with using OLS, is that observations are often right-censored.[7]

Duration models, also called *survival, hazard* or *event history* models, are more commonly used in biostatistics. These models deal with the distribution of survival times from an initiating event (such as birth or the acquisition of a disease) to a terminal event (such as death). The applications of these models in the social sciences range from the study of the duration and dissolution of cabinets in parliamentary democracies (King et al., 1990, Box-Steffensmeier and Jones, 2004) to the study of the length and resolution of civil wars (Regan, 2002; Collier et al., 2004, Fearon, 2004). However, the latter has only been conducted using cross-country variation. In contrast, this paper exploits sub-national violence variation to study the determinants of violence episodes *within* a country in war.

[7]Violence was ongoing in 230 municipalities in December 2004, the last period covered by the conflict data used in this paper. This constitutes 9% of the total violence episodes analyzed for the period 1988-2004.

I now present the statistical framework I use for analyzing the duration of violence in Colombian municipalities. Let T_i be a random variable that represents the duration of violence in municipality i (and is measured in *months*), distributed according to the *probability density function* $f(t_i|\mu_i)$. Note that T_i depends on the scale parameter μ_i. The specific mathematical form of $f(t_i|\mu_i)$, the probability that violence in municipality i ends between time t and Δt, depends upon the assumptions on what the data generating process is. Different assumptions of the functional form of $f(t_i|\mu_i)$ imply substantively different subjective judgements on what the underlying behavior of the baseline hazard of peace is. I this section I discuss such implications.

I assume μ_i is linked to a vector of variables X_i, potentially related to the duration of violence in i through a simple linear function: $\mu_i = X_i\beta$, where β is a vector of the effect parameters to be estimated. I estimate them by *maximum likelihood.* Under the assumption that, conditional on μ_i, the duration of violence in i is independent of the duration in other municipalities ($j \neq i$), the likelihood function of n municipalities can be written as:

$$L(\beta|T) = \prod_{i=1}^{n} f(t_i|\mu_i). \tag{1}$$

I now define a few other general concepts that I will use throughout this and the results sections. Let $S(t_i) = 1- F(t_i)$, the complement of the *cumulative density function* of T_i, be the *survivor function*, or the probability that violence in municipality i lasts beyond period t. Also, define $h(t_i) \equiv \frac{f(t_i)}{S(t_i)}$ as the *hazard function*, or the risk (or probability per unit of time) that violence in municipality i ends in period $t + \Delta t$, given its survival up to period t. It follows that $f(t_i)$, is equal to the product of the hazard and the survivor functions: $f(t_i) = h(t_i)S(t_i)$. The probability of violence ending in municipality i between time t and Δt is then the product of the hazard of peace and the probability of surviving the current period. Substituting it in (1) obtains:

$$L(\beta|T) = \prod_{i=1}^{n} h(t_i)S(t_i) \tag{2}$$

Equation (2) has to be corrected for the fact that the observed data could be right-censored. The actual duration of violence in the 230 municipalities in which violence was ongoing in December 2004, the end date of the analysis for this study, is unknown and plausible distributional assumptions on its survival time have to be made.[8] This idea can be

[8]Of course, it would be wrong assuming either that violence ended in 2004 altogether or that it will never end in these municipalities.

formalized as follows. Let $T_i^* \sim f(t_i^*|\mu_i)$ be an unobserved random variable that represents violence duration in i, again with $\mu_i = X_i\beta$. What is observed is the realization t_i according to the following observation mechanism:

$$t_i = \begin{cases} t_i^* \text{ if } t_i^* < C \\ t_i^C \text{ if } t_i^* > C \end{cases}$$

where C is the (common to all municipalities) censoring time (December 2004) and t_i^C is a censoring value. Define δ_i as an indicator that takes the value of 0 if the observation was censored and 1 if violence in i actually ended. With censored observations, the likelihood function in (2) becomes:

$$\begin{aligned} L(\beta|T) &= \prod_{t \leq t^*} h(t_i)S(t_i) \prod_{t > t^*} S(t_i) \\ &= \prod_{i=1}^{n} [h(t_i)]^{\delta_i} S(t_i). \end{aligned} \tag{3}$$

Note that censored units contribute to the likelihood only through the probability of survival. Equation (3) is the likelihood function that needs to be maximized in the context of right-censored duration models.[9]

It is clear that the choice of a particular stochastic component $f(t)$ [and so that of $h(t)$ and $S(t)$], has different implications in terms of the estimates of β. The most widely assumed functional form in the literature is the *Exponential* density function. For instance, King et al. (1990) and Collier et al. (2004) in the context of cabinet and civil war duration respectively, assume that the distribution of T^* is given by an Exponential density. Less common, though also popular, is the *Weibull* density function. An example of the latter is the paper by Fearon (2004), on civil war duration at the cross-country level. These functional forms have implications in terms of the underlying data generating process of T^*, that are worth discussing. For instance, the mathematical form of the exponential function is:

$$f_E(t_i|\mu_i) = \lambda_i \exp(-\lambda_i \cdot t_i). \tag{4}$$

where $\lambda_i = \exp(-\mu_i)$. Under this specification, λ_i is the hazard function and $\exp(-\lambda_i \cdot t_i)$ is the survivor function. Note that the hazard may differ across municipalities but it is constant over time. This is perhaps the most important implication of the Exponential density in the context of duration models: The probability of violence stopping in municipality i,

[9] In practice the log of the likelihood is easier to maximize and gives the same estimates for β and its uncertainty. The log-likelihood associated with (3) is: $\ln L(\beta|T) = \sum_{i=1}^{n} [\delta_i \ln h(t_i) + \ln S(t_i)]$.

conditional on its survival up to the present, is the same regardless of how long violence has lasted. However, given the substance of the problem of how long violence lasts in different parts of a country experiencing persistent armed conflict, assuming a constant chance of peace is restrictive.[10] The Weibull distribution is a generalization of the Exponential that allows the hazard to change over time. Its functional form is:

$$f_W(t_i|\mu_i, \sigma) = \frac{\lambda_i(\lambda_i t_i)^{\frac{1}{\sigma}-1}}{\sigma} \exp\left[(-\lambda_i t_i)^{\frac{1}{\sigma}}\right] \tag{5}$$

where λ_i is defined as above and σ is a shape parameter. It is straightforward to see that (5) reduces to (4) when $\sigma = 1$. In the case of the Weibull distribution, the hazard function is: $h(t_i) = \lambda_i \sigma^{-1}(\lambda_i t_i)^{\frac{1}{\sigma}-1}$ which varies over time. However, it is monotonically increasing (decreasing) if $\sigma < 1$ ($\sigma > 1$). This is less restrictive than the flat hazard implied by the Exponential distribution, but still does not allow for potential non-monotonic changes of peace. In particular, it could be the case that the hazard of violence ending in a given region is neither constant nor increasing or decreasing over time. For instance, it can have an *inverted-U* shape. Arguably, recent violent outbreaks may rapidly fade out if controlled soon enough before violence becomes an absorbing equilibrium. In this case the chances of peace would increase during the first stages of violence. But if violence lasts beyond a threshold it may become persistent and breaking out of the violent equilibrium gets increasingly difficult. Such non-monotonic behavior of the hazard would be better described by a *Lognormal* density function of the form:

$$f_L(t_i|\mu_i, \sigma) = \frac{1}{\sigma t_i \sqrt{(2\pi)}} \exp\left[-\frac{1}{2}\left(\frac{\log(t_i) - \mu_i}{\sigma}\right)^2\right] \tag{6}$$

with parameters defined as above. The Lognormal distribution is much less used in the duration-models literature than the Exponential and Weibull distributions are. However, equation (6) could potentially fit a number of theoretically plausible examples like the aforementioned inverse-U pattern.

Because the Exponential function is a special case of the Weibull (with $\sigma = 1$), in the next section I only report the results that arise from fitting the latter. While I do not report

[10] Although restrictive, there are ways out of this assumption. Collier et al. (2004), for instance, use a 'piecewise' hazard approach that separates out the hazard function into a 'baseline' hazard that does not depend on covariates and does not vary by country but is only a function of time, and a covariate-varying component: $h(t_i) = h^B(t) \exp[-\mu_i(X_{it}\beta)]$. The baseline hazard consistis on dummy variables that capture year-specific deviations from the constant hazard. However, the choice of a particular piecewise hazard is not less *ad hoc* than the choice of a particular distribution.

the maximum likelihood estimates of the ancillary parameter[11], I do test, for every Weibull model fitted, the null-hypothesis that $\sigma = 1$ and hence whether the data should be better described by the more parsimonious Exponential distribution, with no ancillary parameters. In all cases the hypothesis is rejected which suggests that the baseline hazard is not constant over time. However it is still likely that the baseline hazard is actually non-monotonic. I thus also report results fitting a Lognormal distribution instead.[12]

To further check their robustness and also relax both parametric assumptions regarding the hazard of pace, I estimate a *Cox* duration model. Although less efficient than the parametric models when the distribution is correctly specified, Cox models are appealing because they do not assume any functional form of the baseline hazard: What matters is not the distribution of failures (failure of violence = peace, in this case) but their relative ordering. The semi-parametric nature of Cox allows me to relax the potentially restrictive assumptions of the benchmark specifications, such as the conjecture that the conditional probability of conflict termination is either monotonic over time or has an inverted-U shape.

5 Results

5.1 Benchmark: Group-specific variables with no controls

Each of the panels making up Tables 2A through 2C represents a single regression model. There are eight panels per table and each panel comprises a homogeneous group of variables. These report the *independent* effect on the duration of violence across sub-national units, of such groups, including: scale variables related to the variation in size of the municipalities; victimization variables that describe the human cost of the local-level violence; variables that describe the availability of municipal-specific rents; geographic variables capturing time invariant ecology-specific potential determinants; institutional variables and proxies for state presence; social variables capturing potential local-level grievances; variables describing various forms of government intervention at the local level; and land inequality variables including the land ownership Gini and a land polarization index.

The eight panels appear in the three tables (2A, 2B and 2C). What distinguishes one table from the other is the specification of the duration model utilized. Table 2A reports results

[11] Estimates of σ are available on request.

[12] It is worth pointing out that both the Weibull (and hence the Exponential) and the Lognormal distributions are special cases of a distribution called *Generalized Gamma*, so ideally one would like to fit the latter distribution hence making a less subjective and more data-based choice of the right duration model, an approach followed by Box-Steffensmeier and Jones (2004) for the case of cabinet duration. However, with two ancillary parameters, the Generalized Gamma is computationally unstable and I could not consistently estimate it for most of the specifications reported in the paper.

coming from a Weibull distribution, Table 2B fits a Lognormal and Table 2C estimates a Cox proportional hazard model. While the coefficients of the two parametric distributions should be interpreted in terms of the effect of the specific regressor on the *duration of violence*, those associated with the Cox model refer to the *hazard of violence termination* (or hazard of peace).[13] That is, coefficients that have opposite sign in the Cox model *vis-a-vis* the other two models are internally consistent in terms of the direction of the effects.

To make the interpretation clearer, I report on the right of the estimated slope coefficients the marginal effect associated with one standard deviation increase in each one of the significant variables, departing from their mean value.[14] In the case of the parametric distributions fitted in tables 2A and 2B the marginal effect is reported in terms of the *additional duration* (in months) of violent episodes. These effects represent duration changes relative a *baseline duration* coming from evaluating all the explanatory variables of each model at their means (at 0 if dummies). These are reported at the bottom of each panel. In the case of the Cox Proportional Hazard model (Table 2C), since expected duration cannot be computed because of the lack of an underlying parametric distribution, the substantive interpretation of the coefficients is in terms of the hazard of peace (or the hazard of conflict termination). Hence I report the hazard rates resulting from a one standard deviation increase of the explanatory variables relative to the mean values.

Results suggest that without including control and looking only at the effect of group-specific variables, one group at a time, and regardless of the empirical approach, larger municipalities (both in size an population) are associated with longer violent episodes.[15] Focusing on Tables 2A and 2B, a one standard deviation increase in the log of area significantly increases violence duration in 2.8 (2.3) months when fitting a Weibull (Lognormal) distribution. Similarly, a one standard deviation increase in the log of population is associated with violence episodes 4.4 (3.2) months longer. These marginal effects should be interpreted relative to a baseline of 9.9 months (10.3 in the case of the Lognormal). Looking at the Cox results (Table 2C) yields consistent results: The hazard of peace is almost 11 times larger for municipalities one standard deviation larger in terms of the log of area and 16 times larger for municipalities more populated.

[13]Since there is no distribution for the length of violence, T_i, underlying the Cox approach, expected duration cannot be calculated in this case.

[14]For dichotomous variables the marginal effect is computed from 0-to-1 changes of the variable.

[15]Since the aim of this paper is to present a thorough review of the local-level determinants of violence length within a country experiencing a civil war, no attempts to estimate causal effects is made. The empirical exercise reviews the role of a large list of variables without focusing on any one variable in particular ,the causal effect of which to be pinned down by, for instance, finding a suitable instrument. With this caveat in mind the estimated cardinal magnitudes should be interpreted with caution.

Municipalities out of which a larger number of internally displaced people (IDPs) flee are also associated with longer conflict episodes. The opposite, however, happens in municipalities with higher rates of civilian victimization by illegal armed groups (both guerrillas and paramilitaries). Killings by illegal groups (especially paramilitaries) significantly reduce the duration of violence from 1 to 1.7 months approximately regardless of the distribution used (Tables 2A and 2B). Conversely the hazard of peace is between 5 and 8 times larger (Table 2C). This is consistent with the growing consensus among social scientists that targeting civilians in civil wars has a well defined strategic value (Kalyvas, 2006; Vargas, 2010). Civilian killing is often used to spread fear and reduce the support of the enemy. This support usually takes the form of provision of food, shelter, recruits and especially information. The ultimate objective driving the targeting of this 'civilian infrastructure' is generally that of achieving territorial control. Once this control is secured, and there is no contestation by the enemy, violence fades in such territories.

The availability of both legal and illegal rents is significantly associated with longer conflict episodes. Departing from a baseline duration of 7.4 months (7.7 when fitting a Lognormal) a one standard deviation increase in the log of real tax revenue increases violent waves by 1 month (1.4). Put in another way the hazard of peace is about 7 times smaller in these kind of municipalities. The presence of coca crops, the main input in the production of cocaine, is associated with conflict episodes 6.3 (5.9) months longer. The hazard rate is indeed 26 times smaller. While oil fields do not seem to prolong or shorten violence waves at the municipal level, the availability of other legal resources like gold mines do. Gold presence increases conflict duration in 2.2 months (2.4), and reduces the hazard of conflict termination by a little less than 11 times.

Municipalities located higher up in the mountain, those that are on average warmer through the year, and those where rainfall levels are higher witness longer conflict waves (Tables 2A and 2B) and have smaller peace hazards (Table 2C). Similarly, municipalities farther away from the main market hubs are also places where violence lasts significantly longer and have smaller hazard rates.

Turning to de the set of institutional and state presence variables "police presence" refers to the per capita number of police stations at the municipal level. A one standard deviation increase in this variable lowers the duration of conflict by about a month and increases the hazard o peace by about 6 times, suggesting that police presence deters illegal armed activity to some extent. The same does not occur with military presence, as the number of military bases is *positively* associated with the duration of conflict. However the latter result is not robust as it shows up only when fitting a Weibull distribution and it is significant only at the 10 percent level. Municipalities with a one standard deviation higher incidence of financial institutions like banks and other formal money lender community-level institutions are associated with violent waves 1.6 (1.2) shorter relative to a baseline duration of 9.3. The last result could be capturing the effect of economic development.

Poorer municipalities are associated with violence periods longer by about 2.9 (2.3) months from a baseline duration (computed with all social variables evaluated at their mean) of 10.9 (11.1) months. Average education levels follow similar trends although magnitudes are somewhat larger. This could be associated with economic development as could a deterioration of health outcomes which I proxy by the infant mortality rate. An increase in this measure reduces conflict by about a month. This is, however, somewhat contradictory with the robust finding that one standard deviation increase in the rate of secondary enrollment shortens violence waves 1.1 months.

I also check the effect on conflict duration of three variables that I jointly label as proxies "government intervention" and hence are more than any other group of determinants natural policy instruments with which policy makers may try to help inoculate communities from the siege or armed combat. Surprisingly, an independently of their success in the fields they are aimed at, policies design to reduce the amount of illegal cropping[16] appear to have exacerbated other mechanisms associated with longer violence periods. The larger the municipal area covered by the government program of crop substitution with legal products, the longer violent waves last on average. Larger areas covered by the illegal crop eradication program seem to have the same negative effect. While the magnitude of the effect is not too large (from 1.4 additional months to 1.9 depending on the variable of interest and the parametric distribution fitted –relative to a baseline duration of 10.6 months), this does call for caution in the implementation of certain policies, the general equilibrium effects of which should be evaluated. Military attacks by government forces (namely the military and the police) include for instance bombings of camps of alleged enemies. While these attacks constitute another "government intervention" variable, it is however one that is arguably more directly targeted at the reduction of conflict. Indeed, in sharp contrast with crop substitution and eradication programs, government attacks have been successful in shortening violence episodes and scaling up the hazard of peace. This is most probably explained by the extent to which the Colombian government scaled-up these kind of initiatives.[17]

Using a micro-level dataset on land tenure I construct the land polarization index proposed by Esteban and Ray (1994, 2011). Polarization significantly increases conflict duration

[16]Colombia is the number one produce of coca, used to manufacture cocaine, as well as one of the largest producers of poppy plants, used in the production of heroin.

[17]With financial and military aid from the US, from year 2000 an active military campaign has been promoted by the Colombian government to fight insurgents. This aid package is known as *Plan Colombia* an its aim is to cut down the supply of drugs dispatched to the US.

by over 1 month from a baseline duration of a little over 8 months.

Tables 2A to 2C identify a relatively large set of variables that are significantly associated with longer or shorter conflict episodes. This is by an large robust to fitting different parametric duration models. The difference between the models is the underlying assumption about the shape of the baseline hazard. The stability of the estimated $\boldsymbol{\beta}$ parameters associated with the scale μ_i, using both Weibull and Lognormal chain functions suggests that the results are not likely to be model dependent. Moreover, results are also robust is a semi-parametric, Cox proportional hazard model is used instead.

One important potential reason why a relatively large number of determinants seems to explain the variation of the dependent variable is arguably the absence of many potential explantarry variables. In fact that, for presentation purposes, regressions in this section were run separately for each one of the eight sets of determinants. In the next section I explore the robustness of the significant regressor of each set to adding, one by one, the other seven sets of variables.

5.2 Robustness of duration determinants by group

Given the so far apparent robustness of results to the specification of the model, in this section I refrain from reporting coefficients coming from either Weibull or Lognormal duration models and concentrate on the Cox approach which is the less restrictive in terms of underlying assumptions (although at a cost in terms of efficiency). Table 3 (divided for space reasons into 3A, 3B, 3C and 3D) shows the robustness of group specific results to controlling for each of the other 7 groups of variables, one at a time. The p-value of the χ^2 test of joint significance of the"control" variables is reported in brackets on the column specific to each set of controls.

Table 3 (A through D) shows quite convincingly that the significant correlates of violence duration identified in the benchmark results reported on Table 2 survive the inclusion of single-group controls:[18]

i) The top panel of Table 3A shows that the negative association between scale variables and the hazard rates persists. In addition, once controls are added population density becomes significant in most cases: more dense areas are associates with shorter violence episodes. The set of proxies that control for institutions and state presence is jointly non-significant (p-value of 0.15). The bottom panel reveals that the effect of the three victimiza-

[18] Because the goal of Table 3 is to look at which of the significant variables of the previous exercise survive the inclusion of different set of controls, I do not report the hazard-rates marginal effects. I will come back to these in the next subsection.

tion variables is also robust to the inclusion of different sets of controls the hazard of peace is lowered with higher number of IDPs but it increases with more killings of civilians by illegal groups. The land inequality controls are jointly non-significant (p-value of 0.16). iii) The top panel of Table 3B suggest that the results reported on Table 2 for the rent variables survives the inclusion of controls except in the case of the presence of gold mines once land inequality s taken into account. However the land Gini and the land polarization index are jointly non-significant with a p-value of 0.45. iv) The geography variables are less robust to including controls. The distance variables cease to be significant in most cases while the rainfall and altitude variables lose significance in only some cases (Table 3B, bottom panel). v) Turning to Table 3C, the top panel confirms the findings reported on Table 2, namely that the only two institutional variables and proxies of state presence robustly associated with the duration of conflict are the presence of police inspections and financial institutions. vi) The bottom panel, in turn, suggests that the social variables are somewhat less robust to the inclusion of the different control sets. Secondary enrollment is significant in less that half of the specifications. vii) All government intervention variables survive the inclusion of controls and are highly significant (Table 3D, top panel). viii) The bottom panel of Table 3D endorses the outcome of Table 2 that out of the inequality variables, only the land polarization index is a significant determinant of conflict. This is in line with the theoretical and later on empirical results of the polarization and conflict literature [see Esteban and Ray (2011) for a recent review].

5.3 Robustness of the main predictors

The last exercise is the analysis of the joint significance of all the variables that so far have emerged as robust determinants of conflict duration. I therefore first eliminate the dummies for oil and coal presence from the set of economic and rent variables; the distance variables from the geography set; the number of military bases, institutions of law enforcement and fiscal institutions from the state presence set; both primary and secondary enrollment rates from the social variables set; and the land Gini from the inequality set.

Because some of the resulting variables are highly correlated with one another, in order to avoid multicollinearity when estimating a model that includes at the same time all the robust determinants, I further exclude from the final sample of explanatory variables those that are likely to exacerbate this problem. Variables that present partial correlation coefficients higher than 0.5 (matrix not reported) are then eliminated.[19]

[19] I exclude population density because it is highly correlated with the log of the municipality area ($\rho = -0.62$). The log of population is highly correlated with tax revenues, police presence and financial

Table 4 shows that, by simultaneously adding all the robust determinants, the significance of most of them is lost leaving only a handful of variables that survive this stringent test. Most importantly, this is consistent with running different duration models and hence having different underlying assumption about the shape of the baseline hazard. The first two columns report the Weibull results along with the marginal effect of the significant predictors in terms of additional violence duration due to a one standard deviation increase of the variable of interest relative to its mean. The next two columns report estimated coefficients and marginal effects using a Lognormal link function. The results are very robust to changing the parametric underlying distribution with two exceptions: The presence of coca crops is significant and increases conflict duration (by a little over two months relative to a 6.7 months baseline) when fitting the Lognormal *only*. In turn, results using the Weibull distribution suggest that the poverty rate significantly increases conflict duration, but this is not true for the Lognormal.

The Cox results are consistent with those coming from Weibull and Lognormal. This is true even after adding two additional controls (see the second Cox column): i) I include a full set of department and region fixed effects to control for any unobserved time-invariant regional heterogeneity.[20] ii) I also include a variable that serves as a kind of lag of the dependent variable as it indicates how many violence waves had a given municipality experienced, previous to the current wave at each point in time. The latter control is not significant at conventional levels (that is the current violence in places that had violence episodes in the past will be neither longer nor shorter). The inclusion of the region fixed effects and the lag variable rises the significance of the infant mortality variable: the hazard of peace is 2.7 times shorter for places with an infant mortality rate one standard deviation larger than the mean.

6 Conclusion

While the empirical literature of the causes and consequences of civil war been shifting from cross-country correlations to the analysis of sub-national variation, better suited for

institutions. This is likely to be explained by the fact that more populated areas have also a higher economic development, with bigger revenues, a larger police force and more banks. I hence exclude the log of population from the final sample. Elevation is highly correlated with temperature ($\rho = -0.58$) so I eliminate the latter. Presence of coca crops is highly correlated with the number of IDPs leaving the same municipality ($\rho = 0.53$), which I also exclude. Poverty and average years of schooling are negatively highly correlated so I drop the education variable. Police presence and financial institutions are also positively highly correlated. Because government attacks will be accounted for as a proxy of government military activism I eliminate police presence and keep financial institutions.

[20]The over 1,000 Colombian municipalities are grouped in 33 departments.

the individuation of micro-mechanisms, there is no parallel trend in the analysis of civil war duration. This paper presents, for the first time, a within-country analysis of the determinants of violence duration. I focus on the experience of the Colombia, a country that has experienced armed conflict for about five decades, but where local violence at the local level ebbs and flows responding to specific contexts and incentives. Moreover, Colombia is a good laboratory for the study of civil conflicts given the availability of a great amount of good quality micro data on the conflict dynamics.

Using survival models, and after examining a wide range of factors potentially associated with violence duration at the municipal level (including scale variable, victimization measure, economic factors, geographical conditions, proxies for the quality of institutions and state presence, social variables, measures of government intervention, and land inequality measures) this paper identifies the most robust such local incentives. By doing so, the paper abstract for the in depth analysis of the causal effect of any one particular variable, and focuses on the stability of statistical associations of various potential determinants across a range of specifications. Indeed this paper opens up a research agenda that has the ambitious scope of studying the factors that make internal conflict last longer or that help local communities resile the siege of violence. Future work can focus on one particular variable of interest and explore its causal effect on conflict duration by, for instance, finding a plausible source of exogenous variation that constitutes a good instrument. Other potential extensions include the methodologies that allow controlling for spatial correlation, to explore among other things the extent to which long-lasting conflict episodes cluster across neighboring municipalities.

The results of the empirical exercise presented in this paper are of first order policy relevance. While there is not much scope in the design of successful policies of conflict resolution in knowing that larger municipalities, everything else equal, tend to experience longer conflict episodes, other robust associations do open the door for policy speculation and experimenting. Conflict is more difficult to resolve in municipalities that have a larger availability of rents. This includes both legal an illegal rents. Municipal budgets are often predated by illegal actors in frontier areas and illegal crops provide armed groups with large amounts of resources. This calls for a double strategy of resilience that combines the design of mechanisms for budget monitoring and budget transparency with greater efforts for the reduction of illegal crops. The latter policy, however, should be well tailored to avoid opening up other channels that can affect conflict duration. Indeed, the implementation of crop substitution programs seems also to be associated with longer conflict episodes. This is, however, most probably due to the fact that these kind of alternative development programs take place in places highly affected by the presence of illegal crops to begin with.

The strengthening of social policies that help ameliorate local grievances is also likely to be a successful resilience instrument as revealed by the robust negative association between infant mortality and the hazard of peace.

Last but not least places that experienced higher levels of government military intervention during the sample years have experienced much shorter violence waves. This is a very direct channel of policy intervention that has helped inoculate affected communities.

The individuation of the channels that make municipal violence more or less persistent is particularly relevant for policy purposes. Indeed, understanding the reasons why, in the context of nation-wide civil conflict, some regions consistently experience violence while other remain relatively peaceful during the course of the conflict is of first order importance for the design of policies of conflict resolution.

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Table 1: Descriptive Statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent variable					
Duration (months)	2,685	10.03	20.42	1.00	203.00
Duration–uncensored (months)	2,455	8.13	14.95	1.00	192.00
Scale variables					
Log area (Km)	2,685	6.22	1.21	2.86	11.09
Log population (millions)	2,685	9.83	1.00	6.79	15.48
Population density (thousands/Km)	2,685	0.151	0.76	0.00	14.57
Geography variables					
Altitude (thousand meters)	2,666	1.07	1.24	0.00	2.52
Temperature (Celcius)	2,666	22.40	4.50	3.90	28.90
Rainfall (mm)	2,666	2.08	1.06	0.16	9.20
Distance to department capital (thousand Km)	2,635	0.13	0.10	0.00	0.59
Distance to main markets (thousand Km)	2,620	0.35	0.15	0.06	1.09
Economic and rents variables					
Log real tax income, (billions of pesos)	1,811	7.67	1.29	0.40	13.84
Dummy for presence of coca crops	2,679	0.22	0.39	0.00	1.00
Dummy for oil royalties	2,685	0.17	0.37	0.00	1.00
Dummy for coal royalties	2,685	0.07	0.26	0.00	1.00
Dummy for gold royalties	2,685	0.34	0.47	0.00	1.00
Social variables					
Poverty headcount (%)	2,685	56.04	19.43	9.15	100.00
Years of education of *hh* head	2,619	4.70	1.18	0.00	8.50
Gross primary enrollment (%)	2,566	1.28	0.32	0.25	2.71
Gross secondary enrollment (%)	2,620	0.55	0.25	0.00	1.92
Infant mortality (‰)	2,585	48.19	83.00	3.99	1000.00
Institutional variables					
No. police institutions per capita	2,499	0.13	0.10	0.00	1.14
No. institutions of law enforcement per capita	2,489	0.20	0.16	0.00	1.71
No. financial institutions per capita	2,461	0.16	0.13	0.00	1.27
No. fiscal institutions per capita	2,517	0.04	0.06	0.00	1.00
Dummy for military bases	2,268	0.08	0.31	0.00	3.00
Violence variables					
No. IDPs (thousands)	2,685	2.91	4.95	0.00	53.35
No. paramilitary killings	2,685	0.49	2.09	0.00	41.00
No. guerrilla killings	2,685	0.50	4.39	0.00	213.00
Government intervention					
Alternative-crop support (hectares)	2,685	599.96	1390.42	0.00	13088.41
No. Government attacks	2,685	0.24	0.45	0.00	6.00
Eradicated illegal crops (hectares)	2,685	1011.90	4685.62	0.00	83265.2
Land inequality variables					
Land Gini	1,812	0.67	0.12	0.00	0.97
Land polarization	2,166	0.18	0.03	0.00	0.25

Table 2A: Determinants of Violence Duration: Weibull Distribution

	Coeff.	Mg. effect[b]		Coeff.	Mg. effect[b]
Scale variables			***Victimization variables***		
Log area	0.207	2.8	IDPs	0.117	7.7
	(0.038)***			(0.017)***	
Log population	0.380	4.4	Guerr. killings	-0.026	-1.0
	(0.042)***			(0.005)***	
Pop. density	-0.055	–	Param. killings	-0.095	-1.7
	(0.040)			(0.012)***	
Obs./Baseline dur.[a]:	2,685	**9.9**	Obs./Baseline dur.[a]:	2,685	**9.8**
Economic and rent variables			***Geography variables***		
Log real tax rev.	0.132	1.4	Altitude	0.044	0.6
	(0.035)***			(0.020)**	
Coca crops	0.606	6.3	Temperature	0.057	3.1
	(0.105)***			(0.011)***	
Oil fields	-0.161	–	Rainfall	0.090	1.0
	(0.120)			(0.043)**	
Gold mines	0.255	2.2	Dist. to capital	-0.925	-1.0
	(0.096)***			(0.421)**	
Coal mines	-0.109	–	Dist. to markets	0.542	0.8
	(0.154)			(0.298)*	
Obs./Baseline dur.[a]:	1,809	**7.4**	Obs./Baseline dur.[a]:	2,618	**10.6**
Institutional variables			***Social variables***		
Police presence	-1.402	-1.3	Poverty	0.012	2.9
	(0.525)***			(0.003)***	
Military bases	0.261	0.8	Education	0.272	4.2
	(0.154)*			(0.060)***	
Inst. law enforce.	0.541	–	Prim. enrollment	0.170	–
	(0.397)			(0.144)	
Financial insti.	-1.438	-1.6	Sec. enrollment	-0.450	-1.1
	(0.528)***			(0.264)*	
Fiscal institutions	-1.342	-0.8	Child mortality	-0.001	-1.1
	(0.715)*			(0.000)***	
Obs./Baseline dur.[a]:	2,109	**9.3**	Obs./Baseline dur.[a]:	2,532	**10.9**
Government intervention			***Inequality***		
Alt. crop support	0.095	1.5	Land Gini	-0.235	–
	(0.026)***			(0.446)	
Crop eradication	0.035	1.9	Land polarizat.	4.921	1.4
	(0.010)***			(1.611)***	
Gov. attacks	-0.349	-1.5			
	(0.094)***				
Obs./Baseline dur.[a]:	2,685	**10.6**	Obs./Baseline dur.[a]:	1,812	**8.3**

Notes. Robust standard errors clustered at the municipality level are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. [a] Baseline duration (shown in bold) evaluated at the mean RHS variables except for dummies which are evaluated at 0. [b] Marginal effects (reported only for significant determinants) correspond to the *additional* duration (in months) due to an increase in one standard deviation in the variable of interest (or variable evaluated at 1 if dummy).

Table 2B: Determinants of Violence Duration: Lognormal Distribution

	Coeff.	Mg. effect[b]		Coeff.	Mg. effect[b]
Scale variables			***Victimization variables***		
Log area	0.167	2.3	IDPs	0.075	4.6
	(0.031)***			(0.011)***	
Log population	0.272	3.2	Guerr. killings	-0.025	-1.0
	(0.037)***			(0.012)**	
Pop. density	-0.019	–	Param. killings	-0.076	-1.4
	(0.044)			(0.010)***	
Obs./Baseline dur.[a]:	2,685	**10.3**	Obs./Baseline dur.[a]:	2,685	**10.1**
Economic and rent variables			***Geography variables***		
Log real tax rev.	0.096	1.0	Altitude	0.030	0.4
	(0.030)***			(0.009)***	
Coca crops	0.574	5.9	Temperature	0.041	2.2
	(0.092)***			(0.008)***	
Oil fields	-0.044	–	Rainfall	0.078	0.9
	(0.106)			(0.033)**	
Gold mines	0.175	1.4	Dist. to capital	-0.512	–
	(0.077)**			(0.361)	
Coal mines	0.042	–	Dist. to markets	0.528	0.9
	(0.129)			(0.216)**	
Obs./Baseline dur.[a]:	1,809	**7.7**	Obs./Baseline dur.[a]:	2,618	**10.7**
Institutional variables			***Social variables***		
Police presence	-1.195	-1.1	Poverty	0.010	2.3
	(0.368)***			(0.003)***	
Military bases	0.181	–	Education	0.207	3.0
	(0.130)			(0.043)***	
Inst. law enforce.	0.431	–	Prim. enrollment	0.161	–
	(0.311)			(0.120)	
Financial insti.	-1.048	-1.2	Sec. enrollment	-0.395	-1.1
	(0.403)***			(0.201)**	
Fiscal institutions	-0.863	–	Child mortality	-0.001	-0.8
	(0.560)			(0.000)**	
Obs./Baseline dur.[a]:	2,109	**9.3**	Obs./Baseline dur.[a]:	2,532	**11.1**
Government intervention			***Inequality variables***		
Alt. crop support	0.087	1.4	Land Gini	0.056	–
	(0.020)***			(0.424)	
Crop eradication	0.029	1.6	Land polarizat.	4.323	1.2
	(0.006)***			(1.524)***	
Gov. attacks	-0.320	-1.4			
	(0.044)***				
Obs./Baseline dur.[a]:	2,685	**10.7**	Obs./Baseline dur.[a]:	1,812	**8.2**

Notes. Robust standard errors clustered at the municipality level are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. [a] Baseline duration (shown in bold) evaluated at the mean RHS variables except for dummies which are evaluated at 0. [b] Marginal effects (reported only for significant determinants) correspond to the *additional* duration (in months) due to an increase in one standard deviation in the variable of interest (or variable evaluated at 1 if dummy).

Table 2C: Determinants of Violence Duration: Cox Regression

	Coeff.	Mg. effect[a]		Coeff.	Mg. effect[a]
Scale variables			***Victimization variables***		
Log area	-0.093	-10.7	IDPs	-0.053	-23.11
	(0.018)***			(0.008)***	
Log population	-0.174	-16.0	Guerr. killings	0.011	5.0
	(0.021)***			(0.003)***	
Pop. density	0.031	–	Param. killings	0.037	8.0
	(0.020)			(0.005)***	
Observations:	2,685		Observations:	2,685	
Economic and rent variables			***Geography variables***		
Log real tax rev.	-0.056	-6.9	Altitude	-0.022	-2.7
	(0.017)***			(0.008)***	
Coca crops	-0.301	-26.0	Temperature	-0.024	-10.3
	(0.054)***			(0.005)***	
Oil fields	0.059	–	Rainfall	-0.046	-4.8
	(0.056)			(0.019)**	
Gold mines	-0.112	-10.6	Dist. to capital	0.371	3.8
	(0.046)**			(0.194)*	
Coal mines	0.053	–	Dist. to markets	-0.287	-4.1
	(0.068)			(0.129)**	
Observations:	1,809		Observations:	2,618	
Institutional variables			***Social variables***		
Police presence	0.579	6.2	Poverty	-0.005	-9.8
	(0.224)***			(0.001)***	
Military bases	-0.116	–	Education	-0.114	-12.6
	(0.071)			(0.025)***	
Inst. law enforce.	-0.242	–	Prim. enrollment	-0.088	–
	(0.180)			(0.064)	
Financial insti.	0.691	9.5	Sec. enrollment	0.213	5.4
	(0.229)***			(0.112)*	
Fiscal institutions	0.506	–	Child mortality	0.001	5.0
	(0.329)			(0.000)***	
Observations:	2,109		Observations:	2,532	
Government intervention			***Inequality variables***		
Alt. crop support	-0.042	-5.7	Land Gini	0.090	–
	(0.011)***			(0.217)	
Crop eradication	-0.017	-7.5	Land polarizat.	-2.244	-7.0
	(0.004)***			(0.786)***	
Gov. attacks	0.115	5.4			
	(0.033)***				
Observations:	2,685		Observations:	1,812	

Notes. Robust standard errors clustered at the municipality level are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. [a] Marginal effects (reported only for significant determinants) correspond to the proportional increase/decrease in the hazard of peace due to an increase in one standard deviation in the variable of interest (or variable evaluated at 1 if dummy).

Table 3A: Robustness of Determinants by Group: Cox Regression

Panel A1 – **Robustness of scale variables**

Control set:	Victim.	Econ.	Geogra.	Inst.	Social	Interv.	Dist.
Log area	-0.043	0.023	-0.071	-0.062	-0.088	-0.089	0.003
	(0.019)**	(0.030)	(0.021)***	(0.026)**	(0.023)***	(0.018)***	(0.030)
Log pop.	-0.130	-0.269	-0.180	-0.232	-0.218	-0.168	-0.297
	(0.021)***	(0.041)***	(0.022)***	(0.048)***	(0.025)***	(0.020)***	(0.041)***
Density	0.018	0.971	0.035	0.622	0.022	0.039	1.534
	(0.017)	(0.305)***	(0.020)*	(0.250)**	(0.020)	(0.018)**	(0.450)***
p-val vict.	[0.000]						
p-val econ.		[0.000]					
p-val geo.			[0.036]				
p-val insti.				[0.150]			
p-val social					[0.022]		
p-val interv.						[0.000]	
p-val dist.							[0.000]
Observations:	2,685	1,809	2,618	2,109	2,532	2,685	1,812

Panel A2 – **Robustness of victimization variables**

Control set:	Scale	Econ.	Geogra.	Inst.	Social	Interv.	Dist.
IDPs	-0.038	-0.041	-0.051	-0.049	-0.052	-0.055	-0.050
	(0.008)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.008)***
Guerr. killings	0.010	0.009	0.011	0.010	0.010	0.007	0.010
	(0.003)***	(0.002)***	(0.003)***	(0.002)***	(0.003)***	(0.003)**	(0.002)***
Param. killings	0.038	0.035	0.038	0.034	0.036	0.038	0.031
	(0.005)***	(0.006)***	(0.005)***	(0.005)***	(0.005)***	(0.005)***	(0.005)***
p-val scale.	[0.000]						
p-val econ.		[0.000]					
p-val geo.			[0.003]				
p-val insti.				[0.002]			
p-val social					[0.031]		
p-val interv.						[0.000]	
p-val dist.							[0.163]
Observations:	2,685	1,809	2,618	2,109	2,532	2,685	1,812

Notes. Robust standard errors clustered at the municipality level are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. P-values correspond to the χ^2 tests of joint significance of single-group determinants.

Table 3B: Robustness of Determinants by Group: Cox Regression

Panel B1 – **Robustness of economic and rent variables**

Control set:	Scale	Victim.	Geogra.	Inst.	Social	Interv.	Dist.
Log tax	0.003	-0.046	-0.069	-0.052	-0.107	-0.052	-0.077
	(0.022)	(0.017)***	(0.018)***	(0.019)***	(0.020)***	(0.018)***	(0.018)***
Coca crops	-0.239	-0.131	-0.221	-0.243	-0.157	-0.335	-0.234
	(0.064)***	(0.061)**	(0.063)***	(0.056)***	(0.062)**	(0.057)***	(0.065)***
Oil	0.046	0.062	0.102	0.045	0.089	0.049	0.035
	(0.060)	(0.056)	(0.059)*	(0.059)	(0.065)	(0.059)	(0.064)
Gold	-0.085	-0.118	-0.090	-0.088	-0.114	-0.113	-0.066
	(0.046)*	(0.044)***	(0.048)*	(0.047)*	(0.047)**	(0.047)**	(0.059)
Coal	0.070	0.061	0.038	0.028	0.074	0.024	-0.004
	(0.061)	(0.068)	(0.068)	(0.067)	(0.064)	(0.065)	(0.073)
p-val scale	[0.000]						
p-val victim.		[0.000]					
p-val geo.			[0.040]				
p-val insti.				[0.004]			
p-val social					[0.000]		
p-val interv.						[0.000]	
p-val dist.							[0.454]
Observations:	1,809	1,809	1,762	1,669	1,719	1,809	1,379

Panel B2 – **Robustness of geography variables**

Control set:	Scale	Victim.	Econ.	Inst.	Social	Interv.	Dist.
Altitude	-0.018	-0.026	-0.023	-0.014	-0.013	-0.017	-0.031
	(0.014)	(0.010)***	(0.008)***	(0.005)***	(0.009)	(0.006)***	(0.006)***
Temperature	-0.012	-0.017	-0.008	-0.017	-0.020	-0.022	-0.026
	(0.005)**	(0.005)***	(0.006)	(0.005)***	(0.006)***	(0.005)***	(0.005)***
Rainfall	-0.041	-0.012	-0.037	-0.053	-0.036	-0.038	-0.028
	(0.018)**	(0.018)	(0.024)	(0.021)***	(0.020)*	(0.019)**	(0.020)
Dist. cap.	0.094	0.406	-0.241	0.086	0.385	0.377	0.257
	(0.204)	(0.167)**	(0.245)	(0.214)	(0.229)*	(0.194)*	(0.237)
Dist. mkts.	-0.020	0.102	-0.042	0.134	-0.258	-0.220	-0.238
	(0.127)	(0.126)	(0.175)	(0.136)	(0.168)	(0.129)*	(0.154)
p-val scale.	[0.000]						
p-val victim.		[0.000]					
p-val econ.			[0.000]				
p-val insti.				[0.000]			
p-val social					[0.000]		
p-val interv.						[0.000]	
p-val dist.							[0.084]
Observations:	2,618	2,618	1,762	2,098	2,532	2,618	1,778

Notes. Robust standard errors clustered at the municipality level are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. P-values correspond to the χ^2 tests of joint significance of single-group determinants.

Table 3C: Robustness of Determinants by Group: Cox Regression

Panel C1 – **Robustness of institutional variables**

Control set:	Scale	Victim.	Econ.	Geogra.	Social	Interv.	Dist.
Police	0.256	0.495	0.516	0.632	0.651	0.521	0.467
	(0.216)	(0.212)**	(0.272)*	(0.219)***	(0.238)***	(0.229)**	(0.270)*
Mil. bases	0.012	0.03	0.004	-0.070	-0.157	-0.100	-0.118
	(0.074)	(0.079)	(0.075)	(0.068)	(0.075)**	(0.072)	(0.078)
Law enf.	-0.365	-0.297	-0.458	-0.195	-0.300	-0.233	-0.060
	(0.152)**	(0.166)*	(0.207)**	(0.172)	(0.191)	(0.184)	(0.185)
Financial	0.101	0.499	0.673	0.582	0.601	0.656	0.460
	(0.228)	(0.211)**	(0.269)**	(0.221)***	(0.219)***	(0.231)***	(0.247)*
Fiscal	0.298	0.300	0.382	0.372	0.402	0.472	0.359
	(0.311)	(0.315)	(0.399)	(0.316)	(0.327)	(0.331)	(0.352)
p-val scale	[0.000]						
p-val victim.		[0.000]					
p-val econ.			[0.000]				
p-val geo.				[0.000]			
p-val social					[0.017]		
p-val interv.						[0.000]	
p-val dist.							[0.001]
Observations:	2,109	2,109	1,669	2,098	2,040	2,109	1,687

Panel C2 – **Robustness of social variables**

Control set:	Scale	Victim.	Econ.	Geogra.	Inst.	Interv.	Dist.
Poverty	-0.001	-0.001	-0.004	-0.002	-0.002	-0.005	-0.006
	(0.001)	(0.001)	(0.002)**	(0.002)	(0.001)	(0.001)***	(0.002)***
Education	0.048	-0.042	0.015	-0.076	-0.038	-0.101	-0.078
	(0.028)*	(0.025)*	(0.031)	(0.027)***	(0.030)	(0.027)***	(0.030)***
Prim. enroll.	-0.021	-0.016	0.014	-0.032	-0.097	-0.045	-0.106
	(0.067)	(0.067)	(0.076)	(0.066)	(0.067)	(0.066)	(0.074)
Sec. enroll.	0.075	0.055	0.203	0.260	0.257	0.165	0.100
	(0.117)	(0.116)	(0.134)	(0.115)**	(0.122)**	(0.115)*	(0.130)
Child mort.	0.0001	0.0004	0.0003	0.001	-0.0002	0.001	0.0004
	(0.0002)	(0.0002)***	(0.0002)	(0.000)***	(0.0002)	(0.000)***	(0.0002)**
p-val scale.	[0.000]						
p-val victim.		[0.000]					
p-val econ.			[0.000]				
p-val geo.				[0.000]			
p-val insti.					[0.000]		
p-val interv.						[0.000]	
p-val dist.							[0.001]
Observations:	2,532	2,532	1,719	2,532	2,040	2,532	1,724

Notes. Robust standard errors clustered at the municipality level are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. P-values correspond to the χ^2 tests of joint significance of single-group determinants.

Table 3D: Robustness of Determinants by Group: Cox Regression

Panel D1 – **Robustness of intervention variables**

Control set:	Scale	Victim.	Econ.	Geogra.	Inst.	Social	Dist.
Alt. crops	-0.034	-0.032	-0.050	-0.042	-0.039	-0.038	-0.062
	(0.011)***	(0.011)***	(0.011)***	(0.011)***	(0.013)***	(0.011)***	(0.010)***
Eradication	-0.009	0.002	0.002	-0.012	-0.015	-0.011	-0.018
	(0.004)**	(0.005)	(0.004)	(0.005)**	(0.006)**	(0.006)**	(0.006)***
Gov. attacks	0.138	0.178	0.164	0.105	0.167	0.099	0.175
	(0.029)***	(0.032)***	(0.030)***	(0.033)***	(0.027)***	(0.035)***	(0.029)***
p-val scale	[0.000]						
p-val victim.		[0.000]					
p-val econ.			[0.000]				
p-val geo.				[0.000]			
p-val insti.					[0.000]		
p-val social.						[0.000]	
p-val dist.							[0.001]
Observations:	2,685	2,685	1,809	2,618	2,109	2,532	1,812

Panel D2 – **Robustness of inequality variables**

Control set:	Scale	Victim.	Econ.	Geogra.	Inst.	Social	Interv.
Land Gini	0.140	-0.040	-0.031	-0.024	0.046	0.014	0.261
	(0.218)	(0.214)	(0.421)	(0.224)	(0.218)	(0.383)	(0.216)
Land Polar.	-2.305	-1.296	-0.980	-1.561	-2.603	-2.599	-1.718
	(0.715)***	(0.743)*	(1.408)	(0.758)**	(0.779)***	(1.267)**	(0.751)**
p-val scale.	[0.000]						
p-val victim.		[0.000]					
p-val econ.			[0.000]				
p-val geo.				[0.000]			
p-val insti.					[0.000]		
p-val social						[0.000]	
p-val interv.							[0.000]
Observations:	1,812	1,812	1,379	1,778	1,687	1,724	1,812

Notes. Robust standard errors clustered at the municipality level are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. P-values correspond to the χ^2 tests of joint significance of single-group determinants.

Table 4: Joint Significance Robust Determinants

	Weibull		Lognormal			Cox	
	Coeff.	Mg. eff.	Coeff.	Mg. eff.	Coeff.	Coeff.	Mg. eff.
Scale variables							
Log area	0.153	1.4	0.108	0.9	-0.062	-0.108	-12.3
	(0.075)**		(0.055)*		(0.036)*	(0.042)***	
Victimization variables							
Guerrilla killings	0.001	–	-0.005	–	0.001	0.002	–
	(0.004)		(0.008)		(0.002)	(0.002)	
Param. killings	-0.085	-1.1	-0.070	-0.9	0.034	0.028	6.0
	(0.012)***		(0.013)***		(0.006)***	(0.006)***	
Economic and rents variables							
Log real tax rev.	0.135	1.3	0.094	0.8	-0.064	-0.041	-5.1
	(0.046)***		(0.036)***		(0.022)***	(0.022)*	
Coca crops	0.170	–	0.277	2.1	-0.099	-0.145	–
	(0.174)		(0.140)**		(0.090)	(0.112)	
Gold mines	0.041	–	-0.000	–	0.003	0.048	–
	(0.128)		(0.112)		(0.067)	(0.080)	
Geography variables							
Altitude	-0.0004	–	-0.002	–	-0.003	-0.009	–
	(0.022)		(0.017)		(0.011)	(0.013)	
Rainfall	0.042	–	0.027	–	-0.026	-0.026	–
	(0.054)		(0.041)		(0.026)	(0.031)	
Institutional variables							
Financial insti.	-0.479	–	-0.290	–	0.278	0.166	–
	(0.435)		(0.348)		(0.196)	(0.222)	
Social variables							
Poverty	0.007	1.0	0.004	–	-0.003	0.001	–
	(0.004)*		(0.003)		(0.002)	(0.002)	
Child mortality	0.000	–	0.0001	–	0.0001	-0.0003	-2.7
	(0.004)		(0.0003)		(0.0002)	(0.0002)*	
Government intervention							
Alt. crops	0.127	1.3	0.114	1.1	-0.071	-0.042	-5.7
	(0.033)***		(0.0025)***		(0.016)***	(0.014)***	
Eradication	0.002	–	0.004	–	-0.002	0.009	–
	(0.007)		(0.005)		(0.004)	(0.007)	
Gov. attacks	-0.622	-1.6	-0.379	-1.1	0.204	0.196	9.3
	(0.072)***		(0.053)***		(0.035)***	(0.037)***	
Inequality variables							
Land Polar.	1.548	–	1.020	–	-0.792	-1.767	–
	(2.285)		(1.601)		(1.088)	(1.152)	
Previous violence wave in municipality						-0.057	–
						(0.051)	
Dept. & region FE	No		No		No	Yes	
Obs./Baseline dur.:	1,243	**6.7**	1,243	**6.7**	1,243	1,243	

Notes. Robust standard errors clustered at the municipality level are shown in parentheses. *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level. Baseline duration (shown in bold) an marginal effects computed as explained in the notes of tables 2A/B and 2C.