ETHNICITY AND CONFLICT: AN EMPIRICAL STUDY

By JOAN ESTEBAN, LAURA MAYORAL AND DEBRAJ RAY¹ November 18, 2010

Abstract

This paper examines the impact of ethnic divisions on conflict. The analysis relies on a theoretical model of conflict (Esteban and Ray, 2010) in which equilibrium conflict is shown to be accurately described by a linear function of just three distributional indices of ethnic diversity: the Gini coefficient, the Hirschman-Herfindahl fractionalization index, and a measure of polarization. Based on a dataset constructed by James Fearon and data from *Ethnologue* on ethno-linguistic groups and the "linguistic distances" between them, we compute the three distribution indices. Our results show that ethnic polarization is a highly significant correlate of conflict. Fractionalization is also significant in some of the statistical exercises, but the Gini coefficient never is. In particular, inter-group distances computed from language and embodied in polarization measures turn out to be extremely important correlates of ethnic conflict.

¹Esteban: Institut d'Anàlisi Económica, CSIC; joan.esteban@iae.csic.es. Mayoral: Institut d'Anàlisi Económica, CSIC; laura.mayoral@iae.csic.es. Ray: New York University and Institut d'Anàlisi Económica, CSIC; debraj.ray@nyu.edu. Esteban and Mayoral are members of the Barcelona GSE Research Network funded by the Government of Catalonia. They gratefully acknowledge financial support from CICYT project SEJ-2006-00369. Esteban's research is also funded by the Axa Research Fund. Ray's research was funded by the National Science Foundation under grant SES-0962124 and a Fulbright-Nehru Fellowship from the Fulbright Foundation. He is grateful to the Indian Statistical Institute for warm hospitality during a year of leave from NYU. We are particularly thankful to the generosity of James Fearon for giving us access to his unpublished data set, and we are very grateful to Ignacio Ortuño-Ortín, who computed for us linguistic indices based on the *Ethnologue* dataset. They also thank the suggestions received in the presentations at the IAE (CSIC), CEA meeting 2010 at Québec city, and the Workshop on Political Economy and Development 2010 Paris School of Economics. Finally, we are grateful to Borek Vasicek for highly competent research assistance.

1. INTRODUCTION

In this paper we examine the link between different measures of ethnic distribution and social conflict.

The influence of the Marxian paradigm is clearly perceptible in the traditional view that income or wealth inequality is a major potential cause of conflict. Early empirical studies emphasized, accordingly, the personal distribution of income or of wealth indicators such as landownership (see, e.g., Brockett, 1992, Midlarski, 1988, Muller and Seligson, 1987, Muller et al., 1989, and Nagel, 1974), among several others. However, as the survey article by Lichbach (1989) concluded, the empirical results obtained were generally ambiguous, or statistically insignificant.

The emphasis on class differences as a driver of conflict is natural in the sense that the poor might be reasonably expected to harbor strong antagonisms against the rich. Yet the existence of antagonisms is only part of the story. The prevalence of sustained conflict requires those antagonisms to be channeled into organized action, often a tall order when economic strengths are so disparate. The clear economic demarcation across classes is a two-edged sword: while it breeds resentment, the very poverty of the have-nots militates against a successful insurrection, and even then the different skill and occupational niches occupied by capitalist and worker makes effective redistribution across classes a more indirect and difficult prospect.

In contrast, non-economic markers can be used to separate groups of individuals that are economically *similar*, rather than different. Often, the groups who are thus separated belong to similar niches: they are all workers, or tradesmen, or entrepreneurs in the same sector. If such markers become focal, the gains from conflict are more immediate: the losing group can be excluded from the sector in which they directly compete with the winners. Their very economic similarity ensures that "redistribution" from one group to the other does not need to be achieved indirectly.²

This leads to a very different view of social conflict. It could emanate from economic motivations (as in the Marxian paradigm), but find its expression through the divides generated by *non*-economic markers, such as religion, ethnicity, or national/local origins. It could be further exacerbated by hatreds and resentments — perhaps primordial, perhaps owing to a history of violence — that are attached to the markers themselves. This is why scholars such as Brubaker and Laitin (1998), examining the history of internal conflicts in the second half of the twentieth century, are led to remark on "the eclipse of the left-right ideological axis," and the "marked ethnicization of violent challenger-incumbent contests", while Donald Horowitz observes in his monumental treatise (Horowitz, 1985), that

"In much of Asia and Africa, it is only modest hyperbole to assert that the Marxian prophecy has had an ethnic fulfillment."

 $^{^{2}}$ In addition, within-group economic disparities allow the complementary activities of conflict funding and conflict participation to take place. Esteban and Ray (2008) base a theory of ethnic salience in conflict on this premise.

$$F = \sum_{i=1}^{m} n_i (1 - n_i),$$

where n_i is the share of the population belonging to group i = 1, ..., m.

This index was then used as an independent variable in different empirical specifications. Collier and Hoeffler (2004), Fearon and Laitin (2003) and Miguel et al. (2004) adopt the same measure as a potential correlate of conflict.⁴ The connection did not turn out to be at all strong. For instance, Fearon and Laitin (2003) write that

"The estimates for the effect of ethnic and religious fractionalization are substantively and statistically insignificant . . . The empirical pattern is thus inconsistent with . . . the common expectation that ethnic diversity is a major and direct cause of civil violence."

Of course, there is no reason why we should have expected a connection in the first place, even if we were to believe that "ethnic divisions" are connected to conflict. There is no theoretical basis to the supposition that such "divisions" are best captured by a measure of fractionalization. It is a measure taken off the shelf, one that *happens* to yield the expected results for economic growth or public good provision.

The contribution of Montalvo and Reynal-Querol (2005) — MRQ henceforth — is to empirically examine an alternative measure of "ethnic divisions" that is based on theory. They draw on two papers by Esteban and Ray (1994, 1999) —ER henceforth the first axiomatizing a measure of *polarization*,⁵ and the second attempting to relate polarization to conflict via an explicit behavioral model. Esteban and Ray repeatedly stress the point that social conflict is driven not just by inter-group differences but by within-group cohesion, and in so doing they make a case for the family of polarization measures

$$P_{\alpha} = \sum_{i=1}^{m} \sum_{j=1}^{m} n_i^{1+\alpha} n_j d_{ij},$$

where α has a *strictly positive* lower bound,⁶ and $\{d_{ij}\}$ is some measure of inter-group distances. The existence of $\alpha > 0$ is testimony to the fact that group sizes matter over and above the mere counting of individual heads. The latter would happen if α were

³See, e.g., Mauro (1995), Alesina et al. (1999, 2003), and Alesina and La Ferrara (2005).

⁴See Blattman and Miguel (2010) for an extensive survey that discusses these and related literature. ⁵Measures of polarization were independently developed by Esteban and Ray (1994) and Wolfson (1994).

⁶Esteban and Ray (1994) and Duclos, Esteban and Ray (2004) employ different axioms to get at the same class of measures but with somewhat different bounds on the value of α .

zero, leading to the weighted sum of inter-group distances

$$G = \sum_{i=1}^{m} \sum_{j=1}^{m} n_i n_j d_{ij},$$

which is the well-known Gini coefficient. The whole point of the polarization exercise is to stay away from $\alpha = 0$, and indeed Esteban and Ray (1994, 1999) emphasize the particular case of $\alpha = 1$:

$$P \equiv P_1 = \sum_{i=1}^{m} \sum_{j=1}^{m} n_i^2 n_j d_{ij},$$

which will play a central role in this paper.

In line with P, Reynal-Querol (2002) studied the case in which all inter-group distances are binary, leading to the following specialization of P:

$$R = \sum_{i=1}^{m} n_i^2 (1 - n_i).$$

This is the measure used by MRQ. They show — in an empirical framework very similar to the ones used by Collier and Hoeffler (2004) and Fearon and Laitin (2003) — that R indeed matters for ethnic conflict, while F is not significant. The MRQ paper is important because it provides the first piece of econometric support for the proposition that while fractionalization may not matter for conflict, "deep cleavages" along large group lines — captured by a measure of polarization — might indeed be important.⁷

While, as explained, F and R are very different measures of ethnic divisions, they have an important feature in common. Both measures are based on group sizes *alone*, and do not make use of variations in inter-group "distances". Common sense tells us — and the model we later develop will make it transparent — that if all groups are engaged in a contest to seize private divisible resources, then neglecting distances is indeed the right approach. After all, the contest is a binary question of win or lose.

But groups are not always thus engaged. The contest may be over cultural supremacy, or ideology, or political power, or the control of an economic sector, or more generally over the provision of public goods. In that case the identity of the ultimate winner matters to a losing group, because the "public good" that the winner implements will generate payoffs to the loser. The degree of such "mattering" can be identified with a primal notion of distance, though it may be more general than a metric in the mathematical sense.⁸

⁷In this context, it is worth recalling the observation of Horowitz (1985) that "A centrally focused system [with few groupings] possesses fewer cleavages than a dispersed system, but those it possesses run through the whole society and are of greater magnitude."

⁸Fearon (2003) has already made the point that ethnolinguistic distances may potentially play a role in explaining ethnic conflict and computed a measure based on dissimilarity between pairs of languages. MRQ use Fearon's data to argue that the correlation between G (that uses distances) and F (that doesn't) is 0.82. However, Desmet et al. (2009) re-examine this point in a different context:

This discussion brings us back to the point that most of the literature has been geared towards finding empirical regularities rather than examining the implications of a fully specified model of conflict. Should fractionalization enter the empirical specification? When should we employ the Gini, or polarization, or yet some other measure of ethnic distribution? When should we use distances? Theory should inform these choices.

There is an additional reason for using a fully-developed model, which is that it assists us in the specification and interpretation of an empirical relationship. As an example of the role played by structural constraints, recall the argument of MRQ which shows that not only are R and F conceptually different, they are very different in the data. A scatterplot of R on F shows that the former is empirically related to the latter in inverse-U form (Figures 1–3, MRQ, p. 802–3). But, of course, if one posits that RQ is a quadratic function of F, one obtains extremely high correlations. It follows that if there is no *structural* reason to discard a nonlinear relationship, we should conclude that their result that R, not F, is significant for explaining the incidence of conflict, could be upturned had we explained conflict by means of a second degree polynomial function of fractionalization instead. Without a theoretical model that establishes structural constraints on the equation to be estimated, there seems to be a very modest scope for progress.

With these remarks as background, we turn to a summary of our paper. We build on a general model of conflict developed in Esteban and Ray (2010). In this framework, there is conflict over the control of resources by one of several ethnic groups. The winner in that conflict obtains two sorts of prizes (the ratio between the two prizes is a parameter of the model). First, the winner gets to "produce" a mix of public "goods" — access to an economic sector or a housing market, religious or cultural norms, political power that benefits its own ethnicity. Second, the winner simply gets a divisible resource which can be privately consumed by group members.

A key idea behind this specification is that with private resources, a losing group obtains a payoff that is independent of the identity of the winner.⁹ With public goods to be produced, the identity of the winner matters to the loser and precipitates a notion of "distance" across groups. A second crucial difference between the privateand public-goods cases is that the per-capita payoff in the former depends on group size (the prize needs to be divided up), while no such effect exists for public goods.

Esteban and Ray prove that the equilibrium intensity of conflict can be proxied by a linear function of exactly three indices: F, G, and P, where G and P embody "distances" d_{ij} that are defined by the public goods utility loss to group i should group j win the contest. In particular, the structural feature of the model rules out any specification that is nonmonotonic in F, thereby taking care of the critique in the example discussed above.

the level of social transfers in ethnically heterogeneous societies. They find that the measures that include distances outperform the ones that don't. Specifically, they obtain that G is significant while F isn't and that the same is true for P relative to R.

⁹Sheer resentment at a particular group grabbing the spoils can be viewed as part of the public component of the price.

As we show below and explain in some detail, the weights in the linear expression depend on two fundamental characteristics of the model: the degree of publicness in the group's objectives and level of commitment to the group vis-a-vis the self. These coefficients, once estimated, give us an indirect indication of the role of publicness and the extent of group cohesion in individual behavior.

To estimate the model, the empirical exercise must necessarily make use of intergroup distances, capturing the payoff losses across the different type of public goods preferred by each group.¹⁰ There are two basic difficulties in obtaining such measures of distance. First, we do not have concrete data on what these preferences are, though such an exercise is not beyond the realm of possibility.¹¹ The second difficulty is more fundamental. A direct elicitation of inter-group preferences would necessarily be plagued by endogeneity. It is reasonable and entirely likely that two groups affected by a long history of conflict will have developed preferences that lead to sizable "distances". There is little doubt that measures based on such distances will show large correlations with conflict, but there is little hope of interpreting those coefficients from any causal perspective.¹²

We must therefore trade off an "accurate" description of preferences for something that is a good proxy, and yet possesses a reasonable degree of exogeneity with respect to current conflicts. Following Fearon (2003) and Desmet et al. (2009, 2010), we use linguistic distances across groups as (linear) proxies for the utility losses. We measure the similarity of languages by the relative number of shared branches on the language tree they inhabit (more below) and attempt to capture "cultural" differences over public goods by the degree of linguistic dissimilarity (one minus the resemblance).

We use two different data sources. One is the data compiled by Fearon (2003) for every country: he identifies distinct groups by aggregating across communities with little or no linguistic differences, though these aggregations are qualified and informed by other criteria, mainly religion.¹³ The second source is the inventory of the different linguistic groups at the most disaggregated level possible furnished by the *Ethnologue* project.¹⁴ This permits us to compute distributional measures that depend on intergroup distances, such as G or P, using the two alternative sources of data.

A second distinctive feature of our exercise is that we are interested in the *intensity* of conflict, and not just a binary indicator of whether or not society is in some state

 $^{^{10}}$ Easterly and Levine (1997), Alesina et al. (1999) or Alesina and La Ferrara (2005) assume that ethnic groups differ on the preferences over the public goods to be supplied. However, these papers do not attempt to measure the distance in preferences across ethnic groups.

¹¹For instance, an appropriate calibration of the answers to some of the questions in the *World* Values Survey could give us a some purchase on the problem.

¹²That said, we must note that a similar endogeneity problem is present in the very classification of ethnic groups. Perhaps certain ethnic divisions are made salient by the existence of conflict, which forces us, the researchers, to create separate ethnic categories. Below, we attempt to avoid this problem in our robustness checks.

¹³We are in fact using an updated version graciously made available to us by James Fearon.

¹⁴See details at www.ethnologue.com.

of turmoil. The literature that we've referred to has often focused on the existence (or otherwise) of civil war in a particular time period. Certain criteria are used to determine this, the most important of which is the use of various threshold levels of annual deaths (see, e.g., Small and Singer, 1982, Licklider, 1993, Doyle and Sambanis, 2000, Fearon and Laitin, 2003). Some of our specifications use this standard approach, to aid comparison. In other specifications we attempt to smooth out the binary description. We combine different thresholds for civil war used by the Peace Research Institute of Oslo (PRIO) to arrive at a dependent variable with four-step intensity in conflict. We also use the Cross-National Time-Series Data Archive (CNTS), which generates a continuous index of social conflict by using a weighted combination of several indicators, including political assassinations, demonstrations, strikes, and political prisoners. Apart from providing a continuous measure of social unrest, as opposed to using invariably questionable thresholds to divide peace from war, this index has the added virtue of not restricting attention to civil war alone.

Our empirical exercise estimates the model by Esteban and Ray (2010) using the controls standard in the literature. Our basic result is that the polarization measure P is highly significant, the significance of the fractionalization index F is fragile, as it greatly depends on the specification of the model, and that the Gini index is never significant.

The theory allows us to interpret these coefficients to some degree. The fact that P is significant suggests that disputes over public goods, broadly defined, is invariably a feature of social conflicts. Such public goods could be narrowly economic, such as access to a particular trade or a labor market, or they could be of broader scope, such as political power or cultural dominance. The fact that F is generally significant suggests that divisible pecuniary benefits also play a role in conflict, though as we've mentioned the significance of F is not as ubiquitous as that of P.

The *lack* of significance of the Gini coefficient has a more subtle interpretation. It suggests that free-rider problems in conflict are not as important as we might make them out to be. As we shall argue, this lack of significance (together with the importance of P) suggests that behavior in conflict may be notably driven by concern for the fate of the group, rather than by immediate personal interest.

The paper is organized as follows. In Section 2 we describe and give the intuition for the main proposition in Esteban and Ray (2010). Section 3 provides a detailed discussion of how the different variables have been computed and the data sources that have been used. The variables and controls used in the empirical exercise are fully listed in an Appendix. The main empirical results are presented in Section 4. Section 5 is devoted to various robustness tests. Section 6 concludes.

2. Theory

The conceptual background for this paper is based on Esteban and Ray (1999, 2010). They describe a theoretical framework for conflict in which familiar distributional measures play a central role.

There are *m* groups, with N_i the number of individuals in group *i*, and *N* the total population. The groups are fighting to control society.¹⁵ Control brings with it two prizes, the relative magnitudes of which will be of interest to us.

One is a *public prize*: political control, economic policy (such as protectionism versus liberalization), education, cultural values, and so on. The winning group will get to choose these policies or public goods. The other groups may still derive utility from these choices, depending on "how far away" they are from the winning group. We model attitudes to public goods in the following way. A typical member of group i enjoys some exogenous payoff u_{ij} if the ideal policy of group j is chosen. This induces a notion of "distance" across different groups i and j:

(1)
$$d_{ij} \equiv u_{ii} - u_{ij}$$

which is just the *loss* faced by each individual in group i if group j's policy is implemented.

The other prize is *private*: economic goods that can be seized and consumed. These benefits can be access to positions in the public administration, tax cuts [when the groups specialize in different occupations], allocation of licenses, and the like. Private-ness has two important properties. First, the goods are divided up among the members of the winning group, so that as in Olson (1971), group size matters in the enjoyment of the prize. Second, the identity of the winning group is entirely irrelevant to any of the losers. There are no "distances" with private goods.¹⁶

We will need to carry some notion of the *relative* importance of the two prizes. We do this by assigning a weight λ per-capita to the public prize, which we use to scale all the public payoffs u_{ij} , and a corresponding weight of $1 - \lambda$ per capita to the private prize.

Individuals in each group expend resources r (time, money, effort) to influence the final outcome. Write the cost to such expenditure as c(r); assume that c is increasing, smooth, and strictly convex, with $c'(0) = 0.^{17}$ Add individual contributions over each group i to obtain group contribution R_i . We presume that the probability of success for group i is given by

$$p_i = \frac{R_i}{R_N}$$

where $R_N \equiv \sum_i R_i$.¹⁸ The value $\rho = R_N/N$ is per-capita expenditure in society as a whole; this is the measure of *conflict*.

¹⁵In this exercise, we do not model the decision to engage in conflict, and simply presume that society is in a state of (greater or lesser) turmoil. For explicit models of the decision to enter into conflict, see Esteban and Ray (2007, 2008) and Ray (2009).

¹⁶If there are, such as differential degrees of anger over the identity of the winner, we simply include these components under the first of the two prizes.

¹⁷To obtain a unique equilibrium ER also assume $c'''(r) \ge 0$. We will not be concerned with existence and uniqueness in this exposition, and in particular we won't stay away from the interpretation that c could be "close to" linear.

¹⁸If $R_N = 0$, use an arbitrary allocation of win probabilities.

The "direct" payoff, then, to an individual in group i who expends resources r is given by

(2)
$$p_i \frac{(1-\lambda)}{n_i} - \sum_{j=1}^m p_j \lambda d_{ij} - c(r),$$

where $n_i \equiv N_i/N$ is the population share of group *i*. The first term is the expected payoff from the private good. The second term is the expected payoff from the public good, expressed using the losses or distances. The last term is the resource cost.

The model is closed by presuming that every individual has an "extended utility function" (as in Sen, 1966) which places a weight of $1-\alpha$ on direct payoffs, as described in (2), and a weight of α on group payoffs, obtained as the group *aggregate* of all payoffs in (2). As ER observe, the weight α could (but needn't) be interpreted as altruism or concern: α is some reduced-form measure of the extent to which withingroup monitoring, possibly along with promises and threats, manages to overcome the free-rider problem of individual contributions.

A simple manipulation shows that for individual k member of group i the maximization of the extended payoff is equivalent to the maximization of

$$\left[(1-\alpha)+\alpha N_i\right]\left[p_i\frac{1-\lambda}{n_i}+\lambda\sum_{j=1}^m p_j u_{ij}\right]-c(r_i)-\alpha\sum_{\ell\in i;\ell\neq k}c(r_i(\ell))$$

with respect to $r_i(k)$. Recalling our definition of "distance" from *i* to *j*: $d_{ij} \equiv u_{ii} - u_{ij}$, we define (for every *i* and *j*) $\Delta_{ii} \equiv 0$, and $\Delta_{ij} \equiv \lambda d_{ij} + (1 - \lambda)/n_i$ for all $j \neq i$, and let $\sigma_i \equiv (1 - \alpha) + \alpha N_i$. Then our individual equivalently chooses $r_i(k)$ to maximize

$$-\sigma_i \sum_{j=1}^m p_j \Delta_{ij} - c(r_i(k)).$$

The solution to this maximization problem is completely described by the interior first-order condition:

(3)
$$\frac{\sigma_i}{R} \sum_{j=1}^m p_j \Delta_{ij} = c'(r_i(k))$$

An equilibrium of this model is just a Nash equilibrium across all contributions $\{r_i(k)\}$, for each group *i* and every individual $k \in i$. It generates per-capita conflict, measured by $\rho = R_N/N$. This value will be related to the *data* of the problem, summarized by

(a) group population shares (n_i) , as well as total population N;

(b) inter-group "distances" $\{d_{ij}\}$, as in (1);

(c) the importance of the public good λ ; and

(d) the parameter on extended utility, α .

To state ER's main result, define $\gamma_i \equiv p_i/n_i$ for every group *i*. This is a measure of how group win probabilities depart from their demographic share. The ratio γ_i is exactly 1 when there is no such departure. Define

(4)
$$\phi(\gamma_i, \gamma_j, \rho) \equiv \frac{c'(\rho)\gamma_i\gamma_j}{c'(\gamma_i\rho)}.$$

for every i and j, and observe that $\phi(1, 1, \rho) = 1$ for every $\rho > 0$.

We impose the following computational simplification:

[A] Neglect the discrepancy between win probabilities and demographic shares by setting $\phi(\gamma_i, \gamma_j, \rho) \simeq 1$ for every *i* and *j*.

Proposition 1 (Esteban and Ray, 2010). Under the computational simplification [A], equilibrium per-capita conflict ρ is approximately determined as follows:

(5)
$$\rho c'(\rho) = \omega_1 + \omega_2 G + \alpha [\lambda P + (1 - \lambda)F],$$

where

G is the Gini coefficient using distances (d_{ij}) :

$$G = \sum_{j=1}^{m} \sum_{i=1}^{m} n_i n_j d_{ij};$$

P is the squared measure of polarization from the Esteban-Ray family of polarization measures, again using distances (d_{ij}) :

$$P = \sum_{i=1}^{m} \sum_{j=1}^{m} n_i^2 n_j d_{ij};$$

F is the Hirschman-Herfindahl fractionalization index:

$$F = \sum_{i=1}^{m} n_i (1 - n_i);$$

and the weights in (5) are given by $\omega_1 \equiv (1-\lambda)(1-\alpha)(m-1)/N$, $\omega_2 \equiv \lambda(1-\alpha)/N$.

Under the computational simplification [A], the theory yields a remarkable connection between conflict — or rather, some transform of its disutility — and just three distributional measures. ER go on to argue, using both analytical and numerical methods, that despite the computational simplification the formula (5) yields an accurate approximation for "true", i.e., equilibrium, conflict. We do not repeat these arguments here, but simply take equation (5) as a starting point for our analysis.

The weights associated to the three distributional measures depend on the degree of publicness of the prize, as captured by λ , the level of intra-group cohesion, as described by α , and overall population. Moreover, as population grows, the weight on the "intercept term" as well as the Gini coefficient converges to zero. Conflict is proxied by a convex combination of polarization and fractionalization, no matter what the value of cohesion, as long as the latter is positive.

To understand why ER get the combination they do, begin by thinking about pure public goods. From the vantage point of a single member of group *i* and just two groups *i* and *j*, the severity of the tussle at hand is roughly proportional to the potential loss Δ_{ij} that our individual will suffer if group *j* wins, times the threat posed by group *j* (proxied by demographic share n_j). At the same time, the potency or impact of an individual contribution is roughly of the order of N^{-1} , where *N* is overall population. It stands to reason, then, that the (disutility of the) individual's contribution will be related to $n_i \Delta_{ij}/N$.

Consequently, the total population-normalized contributions made by every one from group i is proportional to

(6)
$$n_i n_j \Delta_{ij} / N.$$

The expression (6) is all we need for an intuitive understanding of the proposition. If, for instance, individuals feel no extended utility and all goods are public, then Δ_{ij} is just d_{ij} , and adding all the expression in (6) over all groups i and j, we get

$$\sum_{i}\sum_{j}n_{i}n_{j}d_{ij}/N = G/N,$$

which explains why the Gini coefficient enters, but in progressively weaker form as population becomes large.

Continuing with public goods, we see that with fully extended utility ($\alpha = 1$), our individual effectively internalizes the potential loss to everyone in her group, not just herself. So the potential loss at hand is $\Delta_{ij} = N_i d_{ij}$. Using this in (6), the total population-normalized contribution from group *i* is $n_i n_j N_i d_{ij}/N = n_i^2 n_j d_{ij}$, and added over all groups we get

$$\sum_{i} \sum_{j} n_i^2 n_j d_{ij} = P,$$

which is the squared polarization measure from the Esteban-Ray family. For the special case in which all groups are indifferent over the public goods other than their own, we should have $d_{ij} = 1$, $i \neq j$, and $d_{ii} = 0$, for all *i*. In this case, *P* reduces to the measure *R*, proposed by Reynal-Querol (2002).

With private prizes at stake, and no extended utility, replace Δ_{ij} by $1/n_i$ in the expression (6); once added over all groups one obtains a constant (intercept) term that vanishes with N. Finally, with extended utility, replace Δ_{ij} by N_i/n_i in (6), which gives us just $n_i n_j$. Adding over all groups yields the fractionalization index.

This explains why polarization and fractionalization have the relative weights described in Proposition 1, why the two measures make an appearance only in the presence of extended utility, and why the weight on the Gini coefficient is attenuated by population size.

3. Empirical Implementation: Data and Conceptual Issues

Our goal is to regard (5) in Proposition 1 seriously, and take it to the data.

In order to interpret equation (5) we observe that the payoff (2) is expressed in terms of the private good, "income". Consequently, the terms d_{ij} are the income equivalent of the loss experienced from obtaining public good j instead of i, the most preferred one. Likewise, c(r) is the income equivalent of contributing a level r of effort to conflict [for instance, we can think of r as time devoted to conflict activities]. Notice now that c'(r) —the marginal cost of conflict— also is the marginal rate of substitution between effort and income. Therefore, we can interpret $\rho c'(\rho)$ as the value in income of the resources contributed by an individual contributing ρ , and using $c'(\rho)$ as the "shadow price" of the effort wasted in conflict. On the RHS of (5) we have a linear function of the three distributional indices, G, F, and P, where the terms d_{ij} are to be interpreted as income equivalent of inter-group distances.

We start by examining the possible indicators for the value of the resources wasted in conflict and then deal with the measurement of group size and inter-group distances needed to compute the distributional indices.

3.1. **Conflict.** Most cross country empirical studies on conflict use the data on incidence and onset from the UCDP/PRIO dataset.¹⁹ We shall also make use of this data.²⁰ We are consequently assuming that a larger per capita expenditure in conflict activities produces a higher incidence of conflict, or frequency of onset.

PRIO considers a country to be in a state of conflict when one of the warring parties is the incumbent government and the number of human casualties goes beyond a threshold level within a given time period. All such observations would be cases of *incidence*. A case of conflict *onset* is more demanding: the observation in question would have to be deemed the start of a "fresh episode" of conflict. The literature has been interested in both these variables, and in our exercise we shall consider either form as well.

The PRIO dataset considers three threshold levels that define higher and higher intensities of conflict: low conflict (PRIO25), intermediate conflict (PRIOCW), and war (PRIO1000). The precise definitions are as follows:

PRIO25: between 25 and 999 battle-related deaths in a given year.

PRIOCW: more than 25 battle-related deaths per year and a total conflict history of more than 1000 battle-related deaths, but fewer than 1000 per year.

¹⁹This is a joint dataset of the Uppsala Conflict Data Program (UCDP) at the Department of Peace and Conflict Research, Uppsala University and the Centre for the Study of Civil War at the International Peace Research Institute, Oslo (PRIO). It is available at http://www.prio.no/Data/. See Gleditsch et al. (2002) for a presentation of the dataset and the relevant definitions.

²⁰Correlates of War (COW) is an alternative dataset. It has been used by Collier and Hoeffler (2002), Fearon and Laitin (2003) and Doyle and Sambanis (2000). Yet, as discussed in Sarkees et al. (2003) the data in COW have three limitations: (i) they are less transparent and reliable than UCDP/PRIO, (ii) the data run till 1990, and (iii) the dataset does not include most post-communist countries. Nevertheless, the correlation with UCDP/PRIO at country-year level is 0.66–0.75.

PRIO1000: at least 1,000 battle-related deaths in a given year.

For the recording of conflict incidence, we divide our time span into five year periods and presume that a country displays conflict activity of a given level if in any of the years within that period the corresponding threshold condition has been met.²¹ We start by following the literature in considering just this dichotomous peace-war variable. We run the exercise for all three threshold levels as a robustness check.

As for conflict onset, we follow the PRIO convention and define an onset year to be one in which there have been more than 25 battle-related deaths and at least a certain number of consecutive years before that were incidence-free. This number is taken to be two (ONSET2), at least five previous years of peace (ONSET5), or at least eight previous years of peace (ONSET8). As in the case of incidence, we employ specifications for all three alternative definitions of onset.

The previous measures of conflict can be questioned because our model suggests that the dependent variable should reflect different intensities of conflict. We tackle this problem from two angles. First, using the same dataset as above, we construct a discrete variable of intensity depending on whether the country is below the threshold PRIO25, below PRIOCW, below PRIO1000 or above that level, recorded as 0, 1, 2, 3, respectively. We test the model using this four-step intensity variable.

Our second approach goes a step further. It takes care of the potential objection that the PRIO measures are exclusively based on the number of battle deaths, and that we miss other forms of social conflict (such as assassinations) that may not qualify as "battle-related". We take as such an indicator the *continuous index of social conflict*, ISC, as computed by the Cross-National Time-Series Data Archive (CNTS). It provides a measure of the level of social unrest with no need to define a questionable threshold dividing "peace" from "war". The index ISC is formed by taking a weighted average over eight different manifestations of internal conflict: Assassinations, General Strikes, Guerrilla Warfare, Major Government Crises, Purges, Riots, Revolutions, and Anti-Government Demonstrations, adopted from Rummel (1963). For details of variables and weights, see the Appendix.

We shall take the value of this continuous index of conflict as our dependent variable, thus assuming that this value is proportional to the monetary value of the per capita resources employed.²²

3.2. Distributional Indices. Our core independent variables are the three indices, G, F, and P. As already noted in Proposition 1 and discussed in detail following that proposition, the index G enters the model divided by total population, N. In line with that specification, we use G/N rather than G as the regressor.²³

²¹We note with some misgivings that the PRIO thresholds are not normalized by the population of the country in question, which undoubtedly biases civil wars in favor of large countries. The population control in our exercises should take care of this problem.

²²The correlation between ISC and PRIOCW is 0.45.

²³We express N in millions.

In order to compute our indices we need the size of the relevant groups for every country and a proxy for the "distance" in preferences across groups.

3.2.1. *Groups.* We base our analysis on the data generously furnished by James Fearon. This data set is an update of the earlier contribution in Fearon (2003), which identifies "culturally distinct" groups in 160 countries. Fearon uses various sources standard in the literature and combines them with complementary information about religious groups and other relevant potential social cleavages.

It can be argued that there is potential endogeneity in such a procedure. Yet the cases of Rwanda, Burundi, Somalia, in which there is full homogeneity in language, or of Papua, where no linguistic group reaches 1% of the population, clearly suggest that the definition of the "relevant" ethnic groups demands careful but active intervention by the researcher. We adopt Fearon's dataset because we are persuaded that it is the best available.

At the same time, in order to check for the robustness of our results, we go to the other extreme. We work with entirely ungrouped raw information on the size of different linguistic groups — and linguistic groups alone —provided by *Ethnologue*.²⁴ It retains the information on languages at its maximum level of detail. The *Ethnologue* project lists 6,912 known living languages and gives the population sizes that use each language in each country. Speaking a different language certainly sets a barrier with one's neighbor and can be considered a sound base for differences in preferences for public goods. In this case, we take the linguistic groups as the relevant ethnic groups, with no aggregation of the raw data at all.

3.2.2. *Preferences and Distances*. Next comes the construction of inter-group distances. Ideally, as discussed in Section 2, we would like to have preferences over public goods. We do not have concrete data on what these preferences are, though this may not be an impossibility. More important, a direct elicitation of such preferences would necessarily be plagued by endogeneity: two conflictual groups are likely to have generated sizable inter-group "distances" in their attitudes.

We therefore use as a proxy the "cultural" distances computed by Fearon (2003) and Desmet et al. (2009, 2010). The basic information derives from the linguistic distance between any two groups. Following Greenberg (1956), Fearon and Laitin (1999, 2000), Laitin (2000) and Fearon (2003), we shall use the *linguistic distance* between two groups as an appropriate indicator for their difference in preferences over public goods.

The different languages spoken can be organized in a *language tree* capturing their genealogy. All Indo-European languages, for instance, will belong to a common subtree. Subsequent splits will create further "sub-subtrees" until we reach the current language map.²⁵ *Ethnologue* reports a maximum of fifteen steps of branching in the tree of all

 $^{^{24}}$ The information from *Ethnologue* has already been used for the analysis of conflict by Fearon (2003), Alesina et al. (2003), and Desmet et al. (2009, 2010).

²⁵For instance, Spanish and Basque diverge at the first branch, since they come from structurally unrelated language families. By contrast, the Spanish and Catalan branches share their first 7

laguages, though of course, not all modern language families hit this upper bound along their own evolutionary branch.²⁶

The distance between two "cultures" can be approximated by how far from each other on the tree their two languages are. Specifically, define the similarity between two languages i and j, s_{ij} , as the ratio of the number of common branches to the maximum possible number— fifteen when we consider the entire tree.²⁷ Then, following Fearon (2003) and Desmet et al. (2009), we define the distance between between the two languages, κ_{ij} , as $\kappa_{ij} = 1 - s_{ij}^{\delta}$, for some parameter $\delta \in (0, 1]$.

There appear to be no compelling arguments for choosing a particular value of δ . While Fearon computes linguistic distances using $\delta = 0.5$, Desmet et al. (2009, 2010) use $\delta = 0.05$. We shall take $\delta = 0.5$ as a base, but will also compute distances using $\delta = 0.05$ and $\delta = 1$. In our empirical exercise we shall be implicitly assuming that the distance in preferences d_{ij} is proportional to κ_{ij} and hence will obtain G and P using these intergroup distances.

Fearon's aggregated ethnic-religious groups may contain subgroups speaking different languages. In such a case, he takes as the representative language the one spoken by the largest subgroup. This language is then used to compute the inter-group linguistic distances.²⁸

Summing up, our baseline is Fearon's estimate of the size of the different ethnic groups in the 160 countries he considers, together with his ethnolinguistic distances using $\delta = 0.5$. With this information we compute G, F, and P for every country. As robustness checks, we also use the values 0.05 and 1 for δ . In addition, we contrast our results recomputing the distributional parameters under the assumption that each language constitutes a "group" and using the group sizes supplied by *Ethnologue*, with $\delta = 0.05$ as in Desmet et al. (2009).

3.3. Additional Controls. We use a set of controls that are usually considered in these exercises. In all the specifications, while the dependent variable is the incidence of conflict in each period, the control variables refer to the first year of each period.

The control variables are population (POP), GDP per capita (GDP), dependence on oil exports (OIL), the percentage of mountainous terrain (MOUNT), a dummy variable for noncontiguity of country territory (NCONTIG), and another dummy for democracy (DEM). The justification for each of these controls can be found elsewhere (Fearon and Laitin, 2003, Collier and Hoeffler, 2004, 2008, Miguel et al., 2004, MRQ). Each control

nodes: Indo-European, Italic, Romance, Italo-Western, Western, Gallo-Iberian and Ibero-Romance languages.

 $^{^{26}}$ The interested reader can find a detailed discussion of the construction of the language tree in Desmet et al. (2009).

²⁷If two groups speak the same language, s_{ij} is set to 1.

²⁸One can argue that the coexistence of various languages within a group might weaken its capacity to produce effective collective action or to achieve agreement on which public goods to demand. We leave this issue for future research.

has been of intrinsic interest in at least one contribution, so we report control coefficients in each specification. In a later set of variations, we include regional dummies for Latin America, Asia and sub-Saharan Africa.

A full list of the additional controls is included in the Appendix.

4. Empirical Results: Ethnic Groups and Conflict

In this section we estimate the model implied by equation (5). Our sample includes 131 countries over the period 1960–2008. As mentioned before, this sample has been divided into five-year sub-periods, with the exception of the last one, 2005–2008, which only contains four years. This gives us a total of 1,174 observations. We begin with a benchmark specification of the dependent and independent variables and then proceed to examine several variations.

In our benchmark exercise, the dependent variable is PRIOCW and the independent variables G/N, P and F are computed from Fearon's updated dataset. Reynal-Querol's binary variant on P is included in some of the exercises. A full set of controls is present in each specification.

We are interested in estimating the model

$$\rho c'(\rho)_{it} = X_{1i}\beta_1 + X_{2it}\beta_2 + \varepsilon_{it}, \ i = 1, \dots, C, \ t = 1, \dots, T,$$

where X_{1i} contains the relevant distributional indices and X_{2i} the controls, ε_{it} is an innovation with symmetric pdf, and C and T are the numbers of countries and time periods respectively.

Clearly, we do not observe $\rho c'(\rho)_{it}$. We therefore interpret the previous equation as a latent variable model. So we presume that

(7)
$$P(\text{PRIOCW}_{it} = 1|X_{it}) = P(\rho c'(\rho) > W^*|X_{it}) = H(X_{it}\beta - W^*)$$

where $X_{it} = (X_{1i}, X_{2it})$, W^* is a threshold that plays the role of an intercept in H, β is the vector that contains the coefficients of interest and H is the cumulative distribution function of ε_{it} .

Table 1 reports our baseline results of estimating (7). Columns 1–6 present the estimated coefficients obtained using maximum likelihood in a logit model.²⁹

In all cases, we compute *p*-values using standard errors robust to within-country correlation and heteroskedasticity. These are reported in parentheses below the estimated coefficients.

 $^{^{29}}$ We have also used a probit model and have obtained identical results.

(1)	(2)	(3)	(4)	(5)	(6)
11.445			10.073	8.183	10.336
(0.001)			(0.011)	(0.033)	(0.002)
1.424	1.617	0.751	1.223	0.759	1.037
(0.071)	(0.010)	(0.349)	(0.152)	(0.352)	(0.159)
-5.851			-5.409		
(0.110)			(0.117)		
		8.916	2.444	4.032	
		(0.014)	(0.550)	(0.335)	
-0.575	-0.456	-0.628	-0.605	-0.646	-0.602
(0.016)	(0.024)	(0.003)	(0.007)	(0.003)	(0.009)
0.184	0.380	0.425	0.211	0.407	0.387
(0.282)	(0.002)	(0.000)	(0.195)	(0.001)	(0.001)
0.708	0.831	0.726	0.691	0.677	0.704
(0.135)	(0.070)	(0.110)	(0.141)	(0.145)	(0.134)
0.007	0.016	0.011	0.006	0.010	0.011
(0.351)	(0.018)	(0.132)	(0.397)	(0.201)	(0.144)
1.264	0.901	1.129	1.281	1.264	1.235
(0.026)	(0.066)	(0.029)	(0.024)	(0.028)	(0.034)
-0.247	-0.151	-0.227	-0.253	-0.235	-0.215
(0.405)	(0.608)	(0.446)	(0.396)	(0.430)	(0.468)
-1.772	-5.576	-5.600	-2.093	-5.157	-5.000
(0.506)	(0.009)	(0.014)	(0.437)	(0.028)	(0.029)
0.217	0.168	0.191	0.218	0.208	0.205
Logit	Logit	Logit	Logit	Logit	Logit
131	131	131	131	131	131
1174	1174	1174	1174	1174	1174
	$\begin{array}{c} (1)\\ 11.445\\ (0.001)\\ 1.424\\ (0.071)\\ -5.851\\ (0.110)\\ \end{array}\\ \begin{array}{c} -0.575\\ (0.016)\\ 0.184\\ (0.282)\\ 0.708\\ (0.135)\\ 0.007\\ (0.351)\\ 1.264\\ (0.026)\\ -0.247\\ (0.405)\\ -1.772\\ (0.506)\\ \end{array}\\ \begin{array}{c} 0.217\\ Logit\\ 131\\ 1174\\ \end{array}$	$\begin{array}{c cccc} (1) & (2) \\ 11.445 \\ (0.001) \\ 1.424 & 1.617 \\ (0.071) & (0.010) \\ -5.851 \\ (0.110) \\ \end{array} \\ \begin{array}{c} -0.575 & -0.456 \\ (0.016) & (0.024) \\ 0.184 & 0.380 \\ (0.282) & (0.002) \\ 0.708 & 0.831 \\ (0.135) & (0.070) \\ 0.007 & 0.016 \\ (0.351) & (0.018) \\ 1.264 & 0.901 \\ (0.026) & (0.066) \\ -0.247 & -0.151 \\ (0.405) & (0.608) \\ -1.772 & -5.576 \\ (0.506) & (0.009) \\ \hline 0.217 & 0.168 \\ Logit & Logit \\ 131 & 131 \\ 1174 & 1174 \\ \end{array}$	$\begin{array}{c cccccc} (1) & (2) & (3) \\ 11.445 \\ (0.001) \\ 1.424 & 1.617 & 0.751 \\ (0.071) & (0.010) & (0.349) \\ -5.851 \\ (0.110) \\ \\ -0.575 & -0.456 & -0.628 \\ (0.016) & (0.024) & (0.003) \\ 0.184 & 0.380 & 0.425 \\ (0.282) & (0.002) & (0.000) \\ 0.708 & 0.831 & 0.726 \\ (0.135) & (0.070) & (0.110) \\ 0.007 & 0.016 & 0.011 \\ (0.351) & (0.018) & (0.132) \\ 1.264 & 0.901 & 1.129 \\ (0.026) & (0.066) & (0.029) \\ -0.247 & -0.151 & -0.227 \\ (0.405) & (0.608) & (0.446) \\ -1.772 & -5.576 & -5.600 \\ (0.506) & (0.009) & (0.014) \\ \hline 0.217 & 0.168 & 0.191 \\ Logit & Logit & Logit \\ 131 & 131 & 131 \\ 1174 & 1174 & 1174 \\ \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$

TABLE 1. BASELINE

Notes: The dependent variable is PRIOCW. P-values are reported in brackets. Robust standard errors adjusted for clustering have been

employed to compute z-statistics.

Column 1 contains our basic specification with the distributional indices P, F and G/N. P has the expected positive coefficient and is significant (at the 1% level). The coefficient associated with F is also positive and significant (at the 10% level or better). In contrast, G/N is not significant. Moreover, in line with a common result in all the literature on conflict with cross-country data, per-capita income is significantly and negatively related to conflict.³⁰

In order to put this result into perspective, we reproduce Fearon and Laitin (2003) and MRQ exercises with our dataset in columns 2 and 3, respectively. We find that F is highly significant, unlike Fearon and Laitin. This result, while of intrinsic interest in guiding our interpretation of the parameters (see below), *is* at odds with the findings in the literature. However, as we shall see, its significance is quite fragile as it critically depends on the particular specification of the model and/or on the definition of conflict being used.

³⁰We have also examined the effect of income inequality. Using the Gini of personal incomes as a regressor has no effect neither on the value of the coefficient corresponding to P nor on its significance, always at 1%.

In column 3 we follow MRQ and add R as a regressor. In line with their results, here too R is indeed highly significant while F stops being so.

This raises the question of whether distances matter at all, once a binary measure of polarization such as R is in place. To explore this matter along with that of the significance of F, we run a new specification in which R is introduced as an additional regressor along with all our existing distributional indices. The results are reported in column 4. The distance-based polarization measure P continues to be highly significant, while the newly-introduced R is not. At the same time, the presence of Rdestroys the significance of F, in line with the findings of MRQ. It is worth noticing that the correlation between R and F is quite high, 0.51. This may induce considerable collinearity between these variables that might explain this outcome.³¹

In our baseline exercise reported in column 1 we have found that G/N was not significant. We now reestimate the model by removing the Gini index from the regression. Columns 5 and 6 display the corresponding results, with and without R, respectively. Removing G/N only from the regression —column 5— we obtain that, while R and F are not significant, P is highly so.

Finally, in column 6 we exclude both G/N and R. We observe that this does not have any impact on either the estimated value of P or on its significance, which remains high. In contrast, the significance of F disappears —as compared with the result in column 1. This result mirrors the one reported by MRQ, where they found that R was significant while F was not, in a specification very similar to the one presented here (we use P instead of R).

If we believe the theory summarized in Proposition 1, it is possible to provide an interpretation for the estimated parameters. Our results show that the coefficient obtained for G/N is not significantly different from zero. This means that $\lambda(1 - \alpha)$ should be very close to zero, where it will be recalled that $\lambda \in [0, 1]$ is the publicness of the prize and $\alpha \in [0, 1]$ the extent of group cohesion.

At the same time, we see that P is highly significant — at a level well below 1% in most of the specifications. That suggests that λ is significantly positive.

Combining these two pieces of information, we must conclude that $\alpha \simeq 1$, indicating that models of free-riding are less relevant than we make them out to be, at least in the cases of collective action in the civil conflicts that we are considering.

Focusing on the estimated coefficients for F and P, we observe that the coefficient of F is not always significant. The non-significance of F, coupled with the high significance of P, implies that there is (at least) an important component of publicness in the winner's return to conflict. Whether that component is economic (control of a labor or housing market, or a trade), cultural (the establishment of some notion of ideological or religious superiority) or political (control of the state) is something we cannot identify; all we can say is that it is central to conflict. At the same time, the

 $^{^{31}\}mathrm{This}$ correlation is even higher in MRQ's dataset, where it is equal to 0.61.

fact that F is significant in some of the specifications suggests that private benefits could also play a role.³²

Stepping back and returning to the strong significance achieved by P, we might think — as Esteban and Ray (1994) did — that there are two distributional features that are relevant for conflict. One is the sense of group *identity*, captured here by an increasing function of group size. To be sure, this effect is nonmonotonic: it kicks in only when other sizable groups are present. The second is "alienation" across groups, measured by inter-group distances. The polarization measures P and R are both sensitive to identity, while F and G are not. Indeed, P and R were deliberately constructed to deal with group size, as well as the possible nonmonotonicity alluded to above. On the other hand, G and P are sensitive to alienation, while F and R are not. The fact that P is highly significant, and in such a dominant way, means that identity and alienation are jointly and synergistically responsible for conflict.

We reiterate that our operative implementation of alienation is not remotely connected with current antagonisms. Such an approach would be immediately vulnerable to claims of endogeneity. We simply stick to language "distances". In this light, the connections appear remarkable.

5. VARIATIONS

In this section we explore the robustness of the previous results to (a) alternative definitions of the dependent variable, (b) other sources of linguistic compositions and distances, (c) other estimation strategies and (d) the possible existence of regional and time effects.

5.1. Other Definitions of Conflict. We begin by checking the robustness of the previous exercise to the use of other definitions of the conflict variable. Recall that the baseline specification uses a binary variable, depending on whether a particular threshold for yearly battle deaths has been crossed. Moreover, we study conflict *incidence* rather than *onset*.

 $^{^{32}}$ This interpretation might be relevant to the discussion of the role of greed versus grievance as motivations for ethnic conflict pioneered by Collier and Hoeffler, see Collier and Hoeffler (2004) and — more recently — Collier et al. (2009).

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Р	$\underset{(0.001)}{11.445}$	$\underset{(0.000)}{9.307}$	$\underset{(0.000)}{13.555}$	$\underset{(0.008)}{4.607}$	$\underset{(0.002)}{5.136}$	$\underset{(0.007)}{4.228}$	$\underset{(0.001)}{9.742}$	$\underset{(0.048)}{3.107}$
F	1.424 (0.071)	$1.517 \\ (0.020)$	$0.808 \\ (0.325)$	1.262 (0.006)	0.640 (0.144)	$\begin{array}{c} 0.671 \\ \scriptscriptstyle (0.130) \end{array}$	1.317 (0.047)	$\underset{(0.321)}{0.345}$
G/N	-5.851 (0.110)	-3.069 (0.084)	-8.302 (0.104)	-1.720 (0.105)	-1.171 (0.221)	-9.421 (0.281)	-3.461 (0.072)	-0.378 (0.497)
LGDPC	-0.575 (0.016)	-0.682 (0.000)	-0.887 (0.000)	-0.408 (0.001)	-0.428 (0.000)	-0.474 (0.000)	-0.640 (0.000)	-0.453 (0.000)
LPOP	0.184 (0.282)	0.187 (0.168)	-0.009 (0.958)	0.060 (0.523)	0.049 (0.563)	0.046 (0.589)	0.155 (0.216)	0.219 (0.000)
OIL	$\underset{(0.135)}{0.708}$	$\begin{array}{c} 0.724 \\ (0.089) \end{array}$	$\underset{(0.151)}{0.681}$	$\underset{(0.001)}{0.939}$	$\underset{(0.004)}{0.633}$	$\begin{array}{c} 0.727 \\ (0.001) \end{array}$	$\underset{(0.097)}{0.675}$	$0.146 \\ (0.478)$
MOUNT	$\underset{(0.351)}{0.007}$	$0.006 \\ (0.304)$	$\begin{array}{c} 0.005 \\ (0.456) \end{array}$	$0.006 \\ (0.153)$	$0.008 \\ (0.048)$	$0.009 \\ (0.024)$	$\underset{(0.263)}{0.007}$	$0.006 \\ (0.084)$
NONCONT	$\underset{(0.026)}{1.264}$	$1.510 \\ (0.000)$	$\underset{(0.017)}{1.305}$	$\underset{(0.000)}{0.913}$	$0.847 \\ (0.001)$	$\underset{(0.003)}{0.752}$	$\underset{(0.002)}{1.265}$	$\underset{(0.002)}{0.699}$
DEM	-0.247 $_{(0.405)}$	$\underset{(0.905)}{0.312}$	-0.430 (0.173)	-0.168 (0.517)	-0.066 (0.795)	$\underset{(0.919)}{0.025}$	-0.137 $_{(0.579)}$	$\underset{(0.458)}{0.100}$
CONST	-1.772 (0.506)	$\underset{(0.802)}{-0.533}$	$\underset{(0.282)}{3.438}$	-0.972 (0.582)	-0.577 (0.712)	-0.270 $_{(0.862)}$	_	$\underset{(0.000)}{5.685}$
$Pseudo-R^2$	0.217	0.209	0.219	0.105	0.073	0.073	0.144	0.236
Est.method	Logit	Logit	Logit	Logit	Logit	Logit	O.Logit	OLS
D.var.	PRCW	PR25	PR1000	ON2	ON5	ON8	PR-INT	ISC
Countries	131	131	131	131	131	131	131	129
Observations	1174	1174	1174	1174	1174	1174	1174	913

TABLE 2. OTHER DEFFINITION OF CONFLICT

Notes: P-values are reported in brackets. Robust standard errors adjusted for clustering have been employed to compute z-statistics. O. Logit: ordered logit.

PR: PRIO (incidence), ON: ONSET, PR-INT: PRIO-INT (intensity)

We go in three directions. First, we use alternative thresholds for the number of deaths. Recall that we worked with PRIOCW, the intermediate intensity of conflict. PRIO also provides data on low and high-intensity conflicts: PRIO25 and PRIO1000, as defined in Section 3.

Second, we examine the notion of onset, instead of incidence. It might be argued (see, e.g., Schneider and Wiesehomeier, 2006) that the factors that contribute to the *outbreak* of a war do not coincide with the ones that keep feeding it. Moreover, once the war has started, the probability that it continues is much higher than the one of a war onset. Thus, it might appear unreasonable to fit a unique model that tries to explain both onset and incidence, since these phenomena will probably have different causes.

In our opinion, this distinction depends on taking the PRIO thresholds very seriously. Before the threshold is crossed, we might have several manifestations of serious conflict (a breakdown in negotiations, an insurgency, a crackdown), so that "onset" as defined by the PRIO threshold is far from a sharp concept: it is arguably no different from a year of "incidence". That said, it is important to consider reasonable alternatives, and the "onset argument" is certainly one of them. We therefore introduce three new dependent variables: ONSET2, ONSET5 and ONSET8. The variable ONSETn switches on if there is intrastate conflict in a particular year using the PRIO25 threshold of with more than 25 annual battle deaths and n years since the last such crossing of the threshold.

The third direction concerns the binary nature of the conflict variable. Proposition 1 establishes a relationship between the three distributional parameters and the *intensity* of conflict. This is imperfectly captured by a binary variable. To be able to capture "intensity" in a more satisfactory manner we take two routes. First, we have constructed a discrete variable (call it PRIO-INT) that takes the values 0, 1, 2, and 3 if the country is below the threshold PRIO25, between PRIO25 and PRIOCW, between PRIO2W and PRIO1000, or above PRIO1000, respectively. Our second route invokes the *continuous index of social conflict*, ISC, that is able to capture small-scale as well as large-scale conflict.

Table 2 presents the results concerning these three directions of enquiry. To facilitate comparison, column 1 reproduces the column 1 in Table 1 for PRIOCW. Columns 2 and 3 employ the alternative PRIO thresholds, leading to the new binary variables PRIO25 and PRIO1000. Columns 4–6 switch to the three new onset variables; the regressions are otherwise identical. Finally, columns 7 and 8 report similar results for the non-binary dependent variables PRIO-INT and ISC. (Ordered logit is used to obtain column 7, while pooled OLS is employed in column 8.) Standard errors robust to within-cluster correlation are employed in all cases.

As in the previous exercise, P invariably enters the regressions with a positive and highly significant coefficient. F has a positive coefficient but it is not always significant: it is so for PRIO25, ONSET2 and ONSET8. The coefficient on G/N is not significantly different from zero in any of the regressions.

5.2. Other Linguistic Distances and Groups. There are different ways of defining distances between languages. For instance, Dyen et al. (1992) use a lexico-statistical analysis to estimate the distances between 95 Indo-European languages.³³ Unfortunately, we cannot use this data since distances are available only for Indo-European languages. However, even within the space of fully-defined language trees, different authors compute distances differently. As mentioned before, the distance between two languages is defined as $\kappa_{ij} = 1 - s_{ij}^{\delta}$, where $\delta \in [0, 1]$. Fearon (2003) suggests the use of $\delta = 0.5$, which is the one that we've employed so far. Desmet et al. (2009) argue that using lower values of δ give intuitively more plausible distances.³⁴ In particular, they

³³They focus on 200 basic meanings and compute for each pair of languages the proportion of *cognates*, that is, the number of times that the two varieties have an unbroken history of descent from a common ancestral form.

³⁴To justify this claim, they provide the following example. Compare the following three language pairs: Italian-Chinese, Italian-Greek and Italian-Spanish. Using $\delta = 0.5$, the relative increase in distance when going from Italian-Spanish to Italian-Greek is larger than when going from Italian-Greek to Italian-Chinese. This apparently counterintuitive result no longer occurs with a $\delta = 0.05$. While we do not necessarily agree with this example, we provide it here for the reader's assessment.

use a value of $\delta = 0.05$. To check that our results are robust to different values of δ employed to compute language distances, we have recomputed P and G using different values of δ .

Table 3 presents the output of reestimating the core specification with these new indices. Column 1 reproduces the benchmark specification presented in Table 1, column 1, computed with $\delta = 0.5$. Columns 2 and 3 present the estimates obtained with $\delta = 0.05$ and $\delta = 1$ respectively. Finally, Desmet et al. (2009) use the information on language compositions provided by *Ethnologue* at the highest level of disaggregation level possible. Indeed, the main difference between *Ethnologue* and other data sources, such as Fearon (2003), is disaggregated detail. For instance, in the case of Mexico, *Ethnologue* reports 291 living languages. In contrast, the number of ethnic groups for this country in Fearon's dataset is four (Mestizo, Amerindian, White and Mayans).

As we've remarked, a fully disaggregated language grouping should not directly correspond to the salient ethnic groups engaged in conflict. But it is also entirely reasonable that the long shadow of history creates connections between the two sets of groupings. As just two examples, consider the use of settler mortality in Acemoglu et al. (2001) as a distant but important correlate of modern-day institutions, or the use of British colonial land collection systems as an explanatory variable for crop productivity in today's India (Banerjee and Iyer, 2005). In both cases, while we fully do not understand the pathways of influence, there is a connection. The advantages of such a connection are obvious: in the main, they permit a more adequate defence of exogeneity.

Similarly, while it is ludicrous to suggest that modern-day conflicts take place across the language groups recorded in *Ethnologue*, it is reasonable to expect that such language distinctions could form the basis of cultural and social distinctions. At the very least, this option is worth examining as a variation. Therefore Column 4 in Table 3 presents the estimates obtained by directly using the indices elaborated by Desmet et al. (2009), with language groupings at their full level of disaggregation. (As in their paper, we use the value of $\delta = 0.05$.)

Variable	(1)	(2)	(3)	(4)
Р	11.445 (0.001)	10.689 (0.001)	10.434 (0.003)	12.103 (0.001)
F	1.424 (0.071)	1.227 (0.123)	1.759 (0.024)	1.612 (0.022)
G/N	-5.851 (0.110)	-4.498 (0.107)	-11.060	-4.756 (0.165)
LGDPC	-0.575 (0.016)	-0.580 (0.009)	-0.520 (0.042)	-0.475 (0.029)
LPOP	0.184 (0.282)	$0.195 \\ (0.228)$	$\underset{(0.376)}{0.160}$	0.290 (0.054)
OIL	$\underset{(0.135)}{0.708}$	$\underset{(0.108)}{0.762}$	$\underset{(0.154)}{0.662}$	$\underset{(0.131)}{0.683}$
MOUNT	$\underset{(0.351)}{0.007}$	$\begin{array}{c} 0.008 \\ (0.326) \end{array}$	$\begin{array}{c} 0.009 \\ (0.188) \end{array}$	$\underset{(0.070)}{0.013}$
NONCONT	1.264 (0.026)	1.234 (0.028)	1.248 (0.027)	0.932 (0.054)
DEM	-0.247 (0.405)	-0.218 (0.463)	-0.331 (0.272)	-0.217 (0.435)
CONST	-1.772 (0.506)	-1.915 (0.483)	-1.561 $_{(0.535)}$	-4.271 (0.104)
$Pseudo-R^2$	0.217	0.212	0.210	0.198
Est.method	Logit	Logit	Logit	Logit
Source	FE (δ =0.50)	FE (δ =1.00)	FE (δ =0.05)	DOW ($\delta = 0.05$)
Countries	131	131	131	134
Observations	1174	1174	1174	1201

TABLE 3. OTHER VARIABLES OF DIVERSITY

Notes: The dependent variable is PRIOCW. P-values are reported in brackets. Robust standard errors adjusted for clustering have been employed to compute z-statistics. Diversity variables source: FE - Fearon (2003), DOW - Desmet et al. (2009).

In all cases, our results are qualitatively identical to what we obtained before: the coefficient on P is invariably similar in sign and size and highly significant. F is generally significant as well. Once again, G/N is never significant.

Now, the fact that computing distances with different values of δ for Fearon's ethnic groups has no effect on the results suggests that variations in the spread of inter-group distances are not critical. It is far more remarkable that, in spite of the very different group composition in *Ethnologue* and the Fearon database, our results survive intact. Indeed, the direct correlation between the two polarization indices (computed from *Ethnologue* and from Fearon) is quite high. For instance, when $\delta = 0.05$ in both cases, the correlation is equal to 0.70. However, the correlation between indices that do not include distances is considerably smaller: for the *R* indices from the two databases, it is equal to 0.34. This makes sense. Without a notion of distance, a further split of groups will affect the measure greatly. With distances, the split is partly ameliorated by the lower linguistic distances between the split groups. This pattern of correlation stresses once more the importance of introducing distances in the computation of distributional measures since they can resolve (in part) the group identification problem. It also possibly accounts for the similarities in the final estimates of the model when either type of data is employed.

5.3. Other estimation strategies. In this section we consider different ways of estimating the conflict equation. Columns 2 and 3 in Table 4 display estimates obtained by applying a random effects and a population-averaged estimators in a logit specification. To facilitate the comparison, column 1 reports estimates obtained in the baseline specification in Table 1. An implication of the theoretical model presented in Section 2 is that the coefficients of F, G/N, and P are country-specific. To account for this, we have allowed for the possibility that the coefficients of each country are random draws from a probability distribution, while those of the remaining variables are still considered to be fixed. Column 4 in Table 4 presents the estimated output, obtained in a linear specification. The coefficients of the distributional indices should be interpreted as the mean values of the corresponding random variables. The conclusions implied by columns 2-4 are very similar: in all cases the coefficients of F and P are positive and highly significant while that of G/N is not.³⁵

Endogeneity in some of the controls is another aspect that is worrisome. In particular, it seems clear that GDP per capita can be endogenous in conflict regressions (Miguel et al., 2004, Djankov and Reynal-Querol, 2010). As in Abadie (2006), we use exogenous variation in landlock (the fraction of a country area distant to sea access) as an instrumental variable for GDP per capita. The identification assumption is that landlock does not cause conflict directly but it is related to conflict only through its effect on income. Column 5 displays the corresponding estimates obtained by 2SLS in a linear model.³⁶ In this case, the coefficient of GDP per capita is very small and insignificant, suggesting that the relation between income and conflict could be spurious.³⁷ However, the coefficient of P is still positive and significant at the 10% level (its p-value is 0.07). The coefficients of F and G/N are not significant in this case.

Columns 6 and 7 use different frequencies for the definition of the variables. Fearon (2005) has criticized the five-year interval used in most empirical studies after Collier and Hoeffler arguing that, since conflict incidence or onset is measured at least annually, the choice of five-year periods is completely arbitrary. We have reestimated our baseline specification using annual data. To this effect, we have used the data in Fearon (2005). Column 6 reports the corresponding estimates.³⁸ Considering annual data does not alter substantially our conclusions. The coefficients of F and P are slighly smaller than in the five-year specification and the former is not significant. However, that of P is still highly significant. Finally, column 7 presents estimates obtained in a cross

³⁵Notice that the magnitudes of the coefficients of columns 2-3 and 4 are not directly comparable since the former have been obtained in a logit specification while the latter, in a linear one.

³⁶The IV-2SLS is typically preferred even when the dependent variable is dichotomous, (see Angrist and Krueger, 2001 and Wooldridge, 2002).

³⁷Similar conclusions have also been reached by Djankov and Reynal-Querol, 2008.

³⁸The dependent variable is annual PRIOcw. Fearon's sample runs from 1960 to 1999. Since annual data on democracy is not available in this sample, its value in the first five-year period, 1960-1965, has been used instead.

sectional regression. In this case, the dependent variable is the average over the 1960-2008 period of PRIOcw, while data on the variables that are not constant over time are referred to 1960. An ordered logit has been employed to obtain the estimates. Regarding the results, the coefficient of P is very similar to that obtained in the yearly specification, positive and significant at the 5% level. In this case, that of F also turns out to be significant while G/N is not.

						~	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Р	$\underset{(0.001)}{11.445}$	$\underset{(0.025)}{15.038}$	$\underset{(0.008)}{8.863}$	$\underset{(0.015)}{1.100}$	$\underset{(0.071)}{1.109}$	$\underset{(0.007)}{8.000}$	$\underset{(0.049)}{8.382}$
F	$\underset{(0.071)}{1.424}$	$\underset{(0.005)}{4.961}$	$\underset{(0.003)}{2.461}$	$\underset{(0.005)}{0.236}$	$\underset{(0.342)}{0.210}$	$\underset{(0.181)}{0.906}$	2.774 (0.010)
G/N	-5.851 (0.110)	-6.357 $_{(0.139)}$	-5.335 (0.118)	-0.103 (0.332)	$\underset{(1.000)}{0.000}$	$\underset{(0.129)}{0.000}$	$\underset{(0.344)}{2.487}$
LGDPC	-0.575 (0.016)	-0.247 $_{(0.408)}$	-0.168 (0.263)	-0.027 (0.097)	-0.014 (0.002)	-0.614 (0.031)	-0.712 $_{(0.031)}$
LPOP	0.184 (0.282)	1.040 (0.001)	0.414 (0.009)	0.049 (0.000)	0.056 (0.001)	0.363 (0.001)	0.077 (0.736)
OIL	$\underset{(0.135)}{0.708}$	-0.185 $_{(0.795)}$	$\underset{(0.908)}{0.042}$	$\underset{(0.324)}{0.041}$	$\underset{(0.532)}{0.071}$	$\underset{(0.227)}{0.530}$	$\underset{(0.058)}{1.344}$
MOUNT	$\underset{(0.351)}{0.007}$	0.021 (0.220)	$0.006 \\ (0.477)$	$\underset{(0.104)}{0.001}$	$\underset{(0.156)}{0.002}$	$\underset{(0.364)}{0.006}$	$\underset{(0.031)}{0.022}$
NONCONT	$\underset{(0.026)}{1.264}$	$\underset{(0.221)}{1.199}$	$\underset{(0.109)}{0.787}$	$\underset{(0.002)}{0.146}$	$\underset{(0.123)}{0.128}$	$\underset{(0.042)}{1.034}$	1.124 (0.080)
DEM	-0.247 (0.405)	-0.416 (0.232)	-0.230 (0.239)	-0.015 (0.539)	-0.066 (0.573)	-0.001 (0.998)	$\underset{(0.670)}{0.239}$
CONST	-1.772 (0.506)	-22.227 (0.000)	-8.854 (0.002)	-0.622 (0.010)	-0.807 (0.557)	-1.770 (0.245)	$\underset{(0.010)}{-0.622}$
$Pseudo-R^2$	0.217	-	-	-	0.167	0.160	0.132
Est.method	Logit	RE	PA	\mathbf{RC}	2SLS	$\operatorname{Logit}^\dagger$	O. Logit [*]
Countries	131	131	131	131	131	129	109
Observations	1174	1174	1174	1174	1174	4472	109

TABLE 4. OTHER ESTIMATION METHODS

Notes: P-values are reported in brackets. Robust standard errors adjusted for clustering have been employed to compute z-statistics.RE: Random Effects; PA: pop-averaged; RC: random coefficients; O. Logit: ordered logit. (†) Yearly data; (*) Cross-Section.

5.4. Robustness to Regional and Time Effects. Finally, we check whether the results are driven by a particular set of countries that can be considered specially conflictual. To do this, we introduce regional dummies for Asia, Latin America and sub-Saharan Africa in the baseline specification. In addition, we simply eliminate these regions (one at a time) from the sample and estimate the corresponding models. Results are presented in Table 5.

Column 1 reproduces once again the benchmark model analyzed in Table 1. Column 2 shows that introducing regional dummies does not change the main results. In Column 3, we eliminate Africa. Now F turns insignificant, and surprisingly, G/N enters with a negative and significant coefficient. The removal of Asian countries in Column 4 has no effect on the results. Similarly, the removal of Latin American

countries from the sample yields a nonsignificant coefficient for F. In all cases, the significance of P remains at the same levels. As a last robustness check, we have introduced a time trend to check whether the existence of time effects can have any impact on our results. This variable takes the values 1, 2, ...,10 for the first, second and tenth periods in the sample. Results are presented in Column 6. Introducing a time trend does not have much impact on either the magnitude of the coefficients or their significance. Hence, similar conclusions as above also hold in this case.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Р	$11.445 \\ (0.001)$	$11.590 \\ (0.003)$	14.056 (0.003)	$11.833 \\ (0.001)$	12.830 (0.002)	$\underset{(0.001)}{12.327}$
F	1.424 (0.071)	$1.588 \\ (0.159)$	1.902 (0.184)	$2.129 \\ (0.029)$	$\underset{(0.096)}{1.373}$	1.272 (0.130)
G/N^*	-5.851 (0.110)	-5.884 (0.118)	-2.040	-5.532 (0.197)	-4.913 (0.126)	-5.722 (0.109)
LGDPC	-0.575	-0.625	-0.627	-0.534	-0.569	-0.621
LPOP	0.184 (0.282)	0.169 (0.249)	-0.038 (0.856)	0.131 (0.677)	$\begin{array}{c} 0.232\\ (0.206) \end{array}$	0.144 (0.397)
OIL	0.708 (0.135)	0.697 (0.134)	$\begin{array}{c} 0.772\\ (0.166) \end{array}$	0.708 (0.188)	1.188 (0.030)	0.602 (0.213)
MOUNT	0.007 (0.351)	0.008 (0.307)	-0.002 (0.891)	0.011 (0.290)	0.009 (0.201)	0.008 (0.312)
NONCONT	1.264 (0.026)	1.236 (0.032)	1.094 (0.092)	1.694 (0.006)	0.905 (0.156)	1.464 (0.014)
DEM	-0.247 (0.405)	-0.189 (0.544)	-0.058 (0.876)	-0.307 (0.391)	-0.108 (0.757)	-0.424 (0.181)
CONST	-1.772 (0.506)	-1.041 (0.785)	2.464 (0.518)	-1.782 (0.650)	-2.796 (0.316)	-1.578 $_{(0.557)}$
$Pseudo-R^2$	0.217	0.219	0.248	0.218	0.234	0.234
Est.method	Logit	Logit	Logit	Logit	Logit	Logit
Regions/ Time	no	reg.dum.	No Africa	No Asia	No L.Am.	time trend
Countries	131	131	92	111	111	131
Observations	1174	1174	813	1002	975	1174

TABLE 5.	Robustness	ТО	REGIONAL	AND	TIME	EFFECTS
----------	------------	----	----------	-----	------	---------

Notes: P-values are reported in brackets. Robust standard errors adjusted for clustering have been employed to compute z-statistics. * Coefficient is in millions.

6. Conclusions

In this paper we examine the link between ethnic divisions and social conflict. There is a large empirical literature on this subject, that we summarize. We argue, as have Esteban and Ray (1994, 1999) and Montalvo and Reynal-Querol (2005), that ethnic polarization is likely to be an important correlate of conflict, rather than the widely used measure of ethnic fractionalization. But the current paper goes significantly beyond this particular argument.

Specifically, we rely on a recent theoretical framework by Esteban and Ray (2010) to argue that conflict can be accurately proxied by a linear combination of polarization,

fractionalization and the Gini coefficient, where the distances used in the first and last measures correspond to the inter-group utility losses in public-goods conflict.

In Section 2, we state this result and explain just why these three indices come into play. We simply note here that the use of distance-based measures is intimately connected to conflict over *public goods*. With public goods, the payoff outcome to a particular group is not binary. The identity of the winner matters to the loser, because (barring very special cases) the mix of public goods implemented by different winners will have different effects on the payoff of a particular loser. This is how the Gini and polarization measures come into play. But the theory goes further: it allows us to interpret the estimated coefficients on each of these measures in terms of the extent of within-group cohesion (as opposed to free-riding) that is present in inter-group conflict. Specifically, the impact of polarization is related to high levels of within-group cohesion.

The theory admits a very different interpretation for conflict over *private* goods. Because private goods are divided up among the winners, the stronger sense of group identity is counterbalanced by the smaller per-capita gains, and polarization measures cease to matter. Fractionalization becomes the main variable that tracks the intensity of such conflicts. But in private goods conflict, distances don't matter: either the winner gets the resources, or does not.³⁹

The theoretical structure both disciplines our empirical research and allows for interpretation of the estimated coefficients. In particular, the estimated coefficients are informative (according to the theory) about the degree of free-riding versus group cohesion, as just discussed. But it is also informative about the degree of conflict that can be attributed to a contest over public goods, versus the goal of seizing divisible private goods. The former can be viewed as a struggle for political power or for cultural or religious dominance, but it could be more than that. Economic outcomes, such as control over entry into a trade or profession, or a housing locality, will also come under the broad rubric of "public goods". Indeed, so will natural resources, to the extent that they are not consumed but used to finance the seizure or maintenance of political power.

A central empirical task of this paper is to implement measures of the Gini and of polarization that employ inter-group distances. We do so using linguistic differences across groups, in the spirit of Fearon (2003) and Desmet et al. (2009). The choice of linguistic distance is driven by the postulate that such distances are plausibly exogenous to conflict, while at the same time they can be expected to drive — or at least influence — antagonisms across groups. Our main identification assumption is that relative linguistic distances across groups are a good proxy for the relative intensity of these antagonisms.

The main result of this paper is that polarization — using linguistic distances — has a large and highly significant impact on conflict across a number of different specifications. This result is robust to all sorts of different measures of conflicts (including

³⁹As mentioned in the paper, different degrees of resentment about the winner of a private-goods conflict can be formally modeled as a public-goods effect.

binary alternatives such as incidence and onset, as well as continuous indices), to alternative ways of calculating language distances, to the choice of groups (as long as language is principally used in defining them), and to the use of different regional dummies or selections. The result is also robust to the inclusion of other measures of ethnic diversity; certainly the fractionalization and the Gini, but also the binary-distance measure of polarization R introduced by Reynal-Querol (2002) and used in Montalvo and Reynal-Querol (2005). This last measure is rendered insignificant once entered into the same regressions along with the distance-sensitive measure of polarization.

The Gini index is also insignificant in most of the specifications, suggesting (along the lines of the theory) that free-riding is not a huge factor in inter-group conflicts. The importance of polarization tells us, in fact, that within-group cohesion is high in conflict.

Finally, the Herfindahl-Hirschman fractionalization index is significant in many of our specifications. Taken along with the results on polarization as well as the theory on which we rely, this suggests that both public-goods and private-goods conflicts are important, though the overwhelming dominance of polarization indicates that publicgoods conflict forms the major component of social tensions.

References

Abadie, A. (2006) "Poverty, Political Freedom, and the Roots of Terrorism," *American Economic Review* **96**, 50–56.

Acemoglu, D., Robinson J. and S. Johnson (2001) "The Colonial Origins of Comparative Development: An Empirical Investigation," *American Economic Review* **91**, 1369–1401.

Alesina, A., R. Baqir, and W. Easterly (1999) "Public Goods and Ethnic Divisions," *Quarterly Journal of Economics*, **114** 1243-1284.

Alesina, A., A. Devleeschauwer, W. Easterly, S. Kurlat and R. Wacziarg (2003) "Fractionalization," *Journal of Economic Growth* 8, 155-194.

Alesina, A. and E. La Ferrara (2005), "Ethnic Diversity and Economic Performance," *Journal of Economic Literature* **43**, 762-800.

Angrist, J and A. Krueger (2001) "Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments," *The Journal of Economic Perspectives* **15**, 69-85.

Banerjee, A. and L. Iyer (2005) "History, Institutions and Economic Performance: the Legacy of Colonial Land Tenure Systems in India," *American Economic Review* **95**, 1190–1213.

Banks, A. S. (2008) "Cross-National Time-Series Data Archive (CNTS) 1815-2007," Databanks International, Jerusalem, Israel.

Blattman, C. and E. Miguel (2010) "Civil War", *Journal of Economic Literature* 48, 3-57.

Brockett, C. D. (1992) "Measuring Political Violence and Land Inequality in Central America," *American Political Science Review* 86, 169-176.

Brubaker, R. and D. D. Laitin (1998) "Ethnic and Nationalistic Violence" Annual Review of Sociology 24, 423-52.

Collier, P. and A. Hoeffler (1998) "On the Economic Causes of Civil War," *Oxford Economic Papers* **50**, 563-573.

Collier, P. and A. Hoeffler (2002) "On the Incidence of Civil War in Africa," *Journal* of Conflict Resolution 46, 13-28.

Collier, P. and A. Hoeffler (2004) "Greed and Grievance in Civil War," Oxford Economics Papers 56, 563-595.

Collier, P., A. Hoeffler, and D. Rohner (2009) "Beyond Greed and Grievance: Feasibility and Civil War," *Oxford Economics Papers* **61**, 1-27.

Desmet, K., I. Ortuño-Ortín, and R. Wacziarg (2009) "The Political Economy of Ethnolinguistic Cleavages," *NBER*, wp n. 15360.

Desmet, K., I. Ortuño-Ortín, and S. Weber (2010) "Linguistic Diversity and Redistribution", *Journal of the European Economic Association* 7, 1291-1318.

Djankov, S. and M. Reynal-Querol (2010) "Poverty and Civil Wars: Revisiting the Evidence", *The Review of Economics and Statistics*. forthcoming.

Doyle, M. and N. Sambanis (2000) "International Peacebuilding: A Theoretical and Quantitative Analysis," *American Political Science Review* **94**, 779-801.

Duclos, J-Y., J. Esteban, and D. Ray (2004) "Polarization: Concepts, Measurement, Estimation," *Econometrica* **72**, 1737-1772.

Dyen, I., J.B. Kruskal and P. Black (1992) "An Indo-European Classification: A Lexicostatistical Experiment", *Transactions of the American Philosophical Society* **82**, Philadelphia: American Philosophical Society.

Easterly W. and R. Levine (1997) "Africa's Growth Tragedy: Policies and Ethnic Divisions," *Quarterly Journal of Economics* **111**, 1203-1250.

Esteban, J. and D. Ray (1994) "On the Measurement of Polarization," *Econometrica* **62**, 819-852.

Esteban, J. and D. Ray (1999) "Conflict and Distribution," *Journal of Economic Theory* 87, 379-415.

Esteban, J. and D. Ray (2007) "Polarization, Fractionalization and Conflict," *Journal of Peace Research* 45, 163-182.

Esteban, J. and D. Ray (2008) "On the Salience of Ethnic Conflict," *American Economic Review* **98**, 2185-2202.

Esteban, J. and D. Ray (2010) "Linking Conflict to Inequality and Polarization," *American Economic Review*, forthcoming.

Fearon, J. (2003) "Ethnic and Cultural Diversity by Country," *Journal of Economic Growth* 8, 195-222.

Fearon, J. (2005) "Primary Commodity Exports and Civil War," *Journal of Conflict Resolution* 49, 483-507.

Fearon, J., and D. Laitin (1999) "Weak States, Rough Terrain, and Large-Scale Ethnic Violence since 1945", Presented at the Annual Meetings of the American Political Science Association, Atlanta, GA.

Fearon, J., and D. Laitin (2000) "Violence and the Social Construction of Ethnic Identity," *International Organization* 54, 845-877.

Fearon, J. and D. Laitin (2003) "Ethnicity, Insurgency, and Civil War," *American Political Science Review* 97, 75–90.

Gleditsch, N-P., P. Wallensteen, M. Eriksson, M. Sollenber, and H. Strand (2002) "Armed Conflict 1946-2001: A New Dataset," *Journal of Peace Research* **39**, 615-37.

Greenberg, J. (1956) "The Measurement of Linguistic Diversity," Language **32**, 109-115.

Horowitz, D.L. (1985), *Ethnic Groups in Conflict*. Berkeley, CA: University of California Press.

Laitin, D. (2000) "What is a Language Community?," American Journal of Political Science 44,142-155.

Lichbach, M. I. (1989) "An Evaluation of *Does Economic Inequality Breed Political Conflict?*," World Politics 4, 431- 470.

Licklider, R. (1995) "The Consequences of Negotiated Settlements in Civil Wars, 1945-1993," *American Political Science Review* **89**, 681-690.

Maddison, A. (2008) "Historical Statistics of the World Economy: 1-2008 AD," http://www.ggdc.net/maddison/.

Mauro, P (1995) "Corruption and Growth," *Quarterly Journal of Economics* **110**, 681–712.

Midlarski, M.I. (1988), "Rulers and the Ruled: Patterned Inequality and the Onset of Mass Political Violence," *American Political Science Review* **82**, 491–509.

Miguel, E., Satyanath, S. and E. Sergenti (2004) "Economic Shocks and Civil Conflict: An Instrumental Variables Approach," *Journal of Political Economy* **112**, 725–753.

Montalvo, J. G. and M. Reynal-Querol (2005), "Ethnic Polarization, Potential Conflict and Civil War," *American Economic Review* **95**, 796–816.

Muller, E.N. and M.A. Seligson (1987) "Inequality and Insurgency," *American Political Science Review* **81**, 425-451.

Muller, E. N., M.A. Seligson and H. Fu (1989) "Land inequality and political violence," *American Political Science Review* 83, 577–586.

30

Nagel, J. (1974), "Inequality and discontent: a non-linear hypothesis," *World Politics* **26**, 453–472.

Olson, M. (1971) *The Logic of Collective Action*. Cambridge MA: Harvard University Press.

Ray, D. (2009) "On the Initiation of Costly Conflict," mimeo., New York University.

Reynal-Querol, M. (2002) "Ethnicity, Political Systems, and Civil Wars", *Journal of Conflict Resolution* 46, 29-54.

Rummel, R.J. (1963) "Dimensions of Conflict Behavior Within and Between Nations," *General Systems Yearbook, VIII*, 1-50.

Sarkees, M. R., F. W. Wayman and J. D. Singer (2003) "Inter-State, Intra-State, and Extra-State Wars: A Comprehensive Look at Their Distribution over Time, 1816-1997," *International Studies Quarterly* **47**, 49D70.

Schneider, G.and N. Wiesehomeier (2006), "Ethnic Polarization, Potential Conflict, and Civil Wars: Comment," unpublished manuscript, University of Konstanz.

Sen, A. (1966) "Labour Allocation in a Cooperative Enterprise," *Review of Economic Studies* **33**, 361-371.

Small, M. and Singer, J.D. (1982) Resort to Arms: International and Civil War, 1816-1980. Sage, Beverly Hills, CA.

Wolfson, M. C. (1994) "When Inequalities Diverge," *American Economic Review* Papers and Proceedings 84, 353-358.

Wooldridge, J. M. (2002), *Econometric Analysis of Cross Section and Panel Data*. The MIT Press.

Appendix

Variables and Weights Used to Compute isc by CNTS. The eight variables included by the CNTS and their weights (in square brackets) are⁴⁰:

- Assassinations (domestic1) [25]: Any politically motivated murder or attempted murder of a high government official or politician.
- General Strikes (domestic2) [20]: Any strike of 1,000 or more industrial or service workers that involves more than one employer and that is aimed at national government policies or authority.
- Guerrilla Warfare (domestic3) [100]: Any armed activity, sabotage, or bombings carried on by independent bands of citizens or irregular forces and aimed at the overthrow of the present regime.
- Major Government Crises (domestic4) [20]: Any rapidly developing situation that threatens to bring the downfall of the present regime excluding situations of revolt aimed at such overthrow.
- Purges (domestic5) [20]: Any systematic elimination by jailing or execution of political opposition within the ranks of the regime or the opposition.
- Riots (domestic6) [25]: Any violent demonstration or clash of more than 100 citizens involving the use of physical force.
- Revolutions (domestic7) [150]: Any illegal or forced change in the top government elite, any attempt at such a change, or any successful or unsuccessful armed rebellion whose aim is independence from the central government.
- Anti-government Demonstrations (domestic8) [10]: Any peaceful public gathering of at least 100 people for the primary purpose of displaying or voicing their opposition to government policies or authority, excluding demonstrations of a distinctly anti-foreign nature.

The calculation of the ISC is performed as follows: weighted sum of occurrences of each event divided by the number of types of variables, 8, and multiplied by 100.

 $^{^{40}}$ For more information, see Banks (2008).

Variables Used in the Empirical Exercises. We summarize the variables used in our empirical exercises and their sources in the following Table.

Variable	Source	Definition
Diversity measures		
- F	FE, DOW	index of fractionalization
- R	FE, DOW	index of polarization - Reynal-Querol (2002)
- P	FE, DOW	index of polarization - Esteban & Ray (1994)
- G	FE, DOW	Gini coefficient
Sociopolitical variables		
- LPOP	MAD, CNTS	log of population (for countries not present in MAD,
		CNTS is used)
- DEM	Polity IV	dummy if democracy score from Policy IV $(1-10)$ is equal
		or higher than 4
Economic variables		
- LGDPC	MAD	log of GDP per capita (in international 1990 dollars)
- OIL	FL	dummy variable for more than 33% of export revenues from oil
		(if country not present in FL, various internet sources are used)
Geography		
- MOUNT	FL	% of the mountainious terrain
- NONCONT	FL	dummy variable for noncontiguous states
Notes: DOW - Desmet	et al. (2009), Fl	E - Fearon (2003), FL - Fearon and Laitin (2003),

TABLE A1. INDEPENDENT VARIABLES

MAD - Maddison (2008);