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Abstract

Somehow paradoxically, it is common for research on the determinants of civil wars to conclude that social factors matter much less, if at all, than economic factors. We contribute to this debate by conducting an original empirical analysis in which we investigate whether the deliberate unequal treatment of groups of people by a government can give rise to movements opposing the current political system. In doing so, we significantly innovate on the existing literature exploring the links between grievances and civil war. We look at all forms of social conflict, violent and non-violent, high and low intensity. Our index of social divisiveness captures multiple dimensions of observed unequal group treatments and is not restricted to latent ethnic divisions. We control for time-invariant factors in a large sample of countries over a long period of time. We take into account measurement uncertainty, dynamics, cross-region heterogeneity, localised spatial effects, non-linearity of effects, and a potential endogeneity bias. Our results show that social divisiveness has a large, positive, and statistically significant robust effect on anti-system opposition. It also appears to be the main channel through which long-lasting ethnic polarisation influences the onset of civil wars.

JEL: D74, H56, P16; **Keywords:** civil resistance, civil war, grievances, social conflict, social divisiveness.

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1 Introduction

Until recently, the politico-economic literature on the determinants of civil wars seemed to have reached a consensus. Explanations centered around economic opportunities for conflict were seen as having a much stronger explanatory power than those based on social grievances (Fearon and Laitin, 2003; Collier et al., 2009; Ray and Esteban, 2017). As highlighted by Cederman et al. (2013), grievance-skepticism was common in other disciplines and was articulated around two core themes. First, grievances are ubiquitous and therefore cannot explain contrasted political situations across countries. Second, grievances are irrelevant once the root causes are considered. Nevertheless, in the last decade, political events and new strands of literature have somehow rehabilitated grievance-based explanations.

In 2011, most of the Middle East and North Africa (MENA) countries had recently experienced declines in relative poverty and expenditure inequality as well as improvements in a number of Millennium Development Goals (Devarajan and Ianchovichina, 2017; Arampatzi et al., 2018). Given these apparently good fundamentals, the 'Arab Spring' uprisings caught the world by surprise (Goodwin, 2011). Among others, Dalacoura (2012), Devarajan and Ianchovichina (2017), and Arampatzi et al. (2018) argue that this outcome, which may have been initially perceived as paradoxical and puzzling, can be easily explained by the growing presence of deep and widespread socio-political grievances in many MENA countries prior to the Arab Spring.

New multi-disciplinary lines of exploration suggest that grievance-based motivations ought not to be dismissed hastily. In Economics, Esteban et al. (2012) point out that traditional proxies for the potential emergence of grievances along ethnic lines, e.g. ethnic fractionalisation or ethnic polarisation, can perform remarkably well when the empirical specification is informed by theory. They highlight that the effects of polarisation are likely to be the consequences of groups trying to gain access to power in order to impose their preferred norms or culture and in that way, possibly, to redress perceived injustices. In Political Science, a literature has emerged around horizontal inequalities, defined as inequalities between groups with shared identities (Stewart, 2008). Empirical evidence is still scarce but existing studies suggest that when some groups (differentiated on the basis of ethnicity, religion, or regions) are, relative to other groups, durably excluded from political power, discriminated against, poorer or less well-educated, they are more likely to engage in a civil war (Østby, 2008; Cederman et al., 2013; Thurber, 2018). Greater attention is also increasingly being paid to the determinants of non-violent resistance campaigns and the successes of these movements relative to violent resistance (Chenoweth et al., 2011; Schock, 2013). Chenoweth and Ulfelder (2017) show that the political salience of elite ethnicity (i.e. whether the ethnic identity of political leaders is a recurring issue of political contention, notably if the political leadership does not represent the largest communal group) is associated with the onset of large non-violent episodes.

Several surveys (Blattman and Miguel, 2010; Ray and Esteban, 2017) have encouraged researchers to explore further the relationship between grievances and social conflict. The purpose of this paper is to answer this call through an innovative empirical analysis. We examine in a comprehensive manner whether the social divisiveness (SOCDIV) generated by deliberate unequal treatment of groups of people by a political regime can give rise to movements opposing the current political system (ANTISYS). With respect to the existing literature, mainly focused on the determinants of civil wars, we innovate in four ways.

First, our dependent variable captures the full spectrum and forms of anti-system opposition. Levels of opposition to the current political regime can range from low (little threat to the regime) to very high (real and present threat to the regime). The movement can be peaceful or armed. We thus cover a much broader variety of social conflicts than studies of civil wars, which are rare and violent events predominantly localised in poor countries. Absence of violence is not equivalent to a lack of social conflict.

Second, our index of social divisiveness provides a much broader and direct coverage of conditions favouring the emergence of grievances than the usual indicators used in the literature. Observed unequal treatment of groups of people by the current political regime is measured across four different dimensions, is not restricted to ethnic divisions, and can range between low and high intensity.

Third, thanks to the large spatio-temporal coverage of our data as well as the granularity of our measures, we can investigate the relationship between social divisiveness and anti-system opposition in 153 countries over the period 1946-2015. In contrast to existing research, we can examine not only how such a relationship varies across countries but also over time, allowing us to account for unobserved time-invariant country heterogeneity. Crucially, the time-series variation of both measures also means that we can control for a potential endogeneity bias by adopting instrumental variables approaches in which lags of SOCDIV can be used as 'internal' instruments for the latter.

Fourth, we exploit various features of our data. We explicitly take into account that our indicators are measured with uncertainty through a multiple imputation approach, we allow for localised spatial effects, and we acknowledge that the impact of social divisiveness may not be same across the distribution of anti-system opposition by estimating conditional and unconditional quantile regressions.

Our results show that social divisiveness has a large, positive, and statistically significant effect on the level of opposition to the current political regime. This result is robust to the presence of fixed effects, dynamics, measurement uncertainty, spatial interactions, other control variables, cross-country heterogeneity, endogeneity bias. Like time-invariant indicators of ethnic polarisation, social divisiveness can explain the onset of civil wars, but unlike these indicators, quantile regressions reveal that social divisiveness plays a role at all levels of social conflict. Overall, adopting a social divisiveness-based approach appears to be extremely informative to understand variations in social conflicts across countries and over time.

This paper contributes to the broad and cross-disciplinary literature on the systematic role that grievances play in various forms of social conflicts: violent or non-violent, low-intensity or high-intensity. Adopting an original approach, we show that grievances do indeed matter. Our results also strongly complement recent analyses of the onset of civil wars, such as the seminal paper of Esteban et al. (2012), which relates longstanding ethnic divisions to violent conflicts. We provide direct evidence that social divisiveness is the main channel through which the effects of ethnic polarisation manifest themselves. On the other hand, we find little evidence for alternative systematic explanations of social conflicts based on inter-personal income inequality (Cramer, 2003) or, more recently in the wake of the Arab Spring, the dissatisfaction of a young educated population confronted with poor economic prospects (Campante and Chor, 2014). It is possible that these relationships are more complex or region-specific (Ray and Esteban, 2017).

The rest of the paper proceeds as follows. In Section 2, we describe our data and the econometric model. In Section 3, we present our results. We provide concluding remarks in Section 4.

2 Econometric model and data

2.1 Econometric model

We estimate the following, baseline, model:

$$ANTISYS_{it} = \gamma_1 SOCDIV_{it-1} + CVAR_{it-1}\beta + \alpha_i + \alpha_t + \epsilon_{it} \quad (1)$$

where $ANTISYS$ is a measure of the strength of popular opposition to the current political system in country i at period t, $SOCDIV$ is a measure of social divisiveness, $CVAR$ is a vector of control variables, αs are country and time fixed effects, ϵ is the error term.

We have available data for 153 countries over the 1946-2015 period. A country is included in the dataset once it is independent.[1] To account for the fact that changes in

[1] Independence dates come from the ICOW Colonial History Dataset (`http://www.paulhensel.`

the political situation take time to happen and to reinforce the direction of causality, we divide the time period into five-year subperiods (1946-1950...2011-2015) and we lag our explanatory variables by one period (e.g. 2011-2015 values for ANTISYS are related to 2006-2010 values of SOCDIV). For ANTISYS, in order not to miss a drastic change in the level of anti-system activity, we take the maximum value within a given period; we will show that taking the average yields the same results. For the other variables, we take the average values.[2]

It is important to note that, relative to previous work, we include country fixed effects α_i. These variables control for all time-invariant factors, reducing in that way the risk of an endogeneity bias. Their inclusion also means that identification of the effects is based on time-series variation in the data. This may have been an issue if our variables of interest were highly persistent. However, our stylised facts, and notably our country-specific examples, highlight that the values of ANTISYS and SOCDIV vary both between and within countries. Furthermore, we will show that we obtain very similar results when we exploit the between-country variation in the data.

We stress that equation (1) is a baseline model. In subsequent analyses, that we describe in the relevant sections, we examine the robustness of our results when:

- we explicitly account for the uncertainty surrounding our measures of ANTISYS and SOCDIV using a multiple imputations approach.
- we control for the persistence of ANTISYS through the estimation of a dynamic panel data model.
- we identify the effects uniquely on the basis of between-country variation.

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org/icowcol.html. A state is considered independent when it is in control of both its domestic and foreign policy.

[2]When taking averages, lagging explanatory variables is important as, otherwise, using contemporaneous averages could mix yearly values for past, current, and future events within a given sub-period. We replicated the regression in column (5) of Table 2 using yearly data: results are very similar with a coefficient on SOCDIV of 0.485, statistically significant at the 1% level.

- we relax the assumption that the effect of SOCDIV is the same across geographical regions.

- we explicitly control for the presence of localised spatial effects.

- we investigate other potential determinants of ANTISYS suggested by the literature, such as income inequality.

- we directly relate them to the empirical analysis of Esteban et al. (2012) on ethnic divisions and the onset of civil wars.

- we adopt instrumental variables approaches, based on external and internal instrument, to deal with any potential endogeneity bias such as reverse causality.

- we allow for the possibility that the effects of SOCDIV vary across its conditional and unconditional distributions.

2.2 Data

Data about our main variables of interest come from the V-dem (Varieties of Democracy) database.[3] In addition to factual data gathered by in-house researchers, external country experts (5-6 per country-year indicator) are asked to provide an evaluation of a large number of characteristics of a given political regime on an ordinal scale. A measurement model is used to aggregate these multiple ratings. It takes into account differences of opinion or judgement errors among country experts and provides point estimates (median values of the probability distributions) and measures of uncertainty. We use values mapped on a linearised ordinal scale. The scale typically ranges from -3 to 3.

Our dependent variable (ANTISYS) corresponds to the responses, subsequently mapped on a linearised ordinal scale, to the following question " *Among civil society organizations, are there anti-system opposition movements?* " Responses, on the original scale,

[3] `https://www.v-dem.net/`

can vary from 0 (no, or very minimal. Anti-system movements are practically nonexistent) to 4 (there is a very high level of anti-system movement activity, posing a real and present threat to the regime).

Anti-system opposition is defined as " *any movement - peaceful or armed - that is based in the country (not abroad) and is organized in opposition to the current political system. That is, it aims to change the polity in fundamental ways, e.g., from democratic to autocratic (or vice-versa), from capitalist to communist (or vice-versa), from secular to fundamentalist (or vice-versa). This movement may be linked to a political party that competes in elections but it must also have a 'movement' character, which is to say a mass base and an existence separate from normal electoral competition.* "

This variable captures the latent possibility that, at any point of time, a large number of citizens organise themselves to change the current rules of the game, peacefully or not. By its very nature, it can pick up anti-system activity which does not manifest itself through extreme events, i.e. revolutions or civil wars, providing in that way a much more granular and comprehensive picture of social conflicts.

Our key explanatory variables reflect four dimensions of social divisiveness, i.e. deliberate unequal treatment of groups of people living in the same country by the political regime. These are the answers to the following questions, subsequently mapped on a linearised ordinal scale (original ordinal scale reported):

1. Particularistic goods (PARTGOODS): " *Considering the profile of social and infrastructural spending in the national budget, how 'particularistic' or 'public goods' are most expenditures?* "; 0 (almost all of the social and infrastructure expenditures are particularistic) to 4 (almost all social and infrastructure expenditures are public goods in character). Particularistic spending only targets a specific set of constituents whereas public goods spending is intended to benefit all constituents.

2. Social group inequality (CIVSOC): " *Do all social groups, as distinguished by language, ethnicity, religion, race, region, or caste, enjoy the same level of civil liber-*

ties, or are some groups generally in a more favorable position? " ; 0 (much fewer) to 4 (same).

3. Social class inequality (CIVINC): " *Do poor people enjoy the same level of civil liberties as rich people do?* "; 0 (much fewer) to 4 (same level).

4. Subnational civil liberties unevenness (CIVREG): " *Does government respect for civil liberties vary across different areas of the country?* "; 0 (yes, significantly) to 2 (no).

Civil liberties cover here access to justice, private property rights, freedom of movement, and freedom from forced labour. They do not cover *political* civil liberties.

The scale of these four indicators is inverted such as a larger value implies more discrimination of some groups in the population. Figure 1 shows that these four dimensions are highly correlated. Hence, without much loss of information, we aggregate them into a single indicator of social divisiveness (SOCDIV) by extracting the first principal component from a principal components analysis.

Figure 1: Correlations between SOCDIV dimensions

PARTGOODS	0.552	0.684	0.475
0.552	CIVSOC	0.727	0.529
0.684	0.727	CIVINC	0.536
0.475	0.529	0.536	CIVREG

A principal components analysis can be understood as a data reduction technique whose purpose is to find normalised linear combinations of a set of variables which retain most of the information provided by these variables. When variables are highly correlated, such as ours, the first linear combination (component) captures most of the total variance, or from a different perspective, the projected observations on the first principal component are very close to the original observations and therefore the first principal component is a good summary of the data. In our case, the first principal component accounts for 69% of the total variance with an eigenvalue (i.e. variance of the component) of 2.76, whereas the second principal component accounts for 14% of the total variance with an eigenvalue of 0.56. A common criterion is to keep principal components with eigenvalues greater than one. In our case, this means discarding all principal components besides the first component.[4]

The SOCDIV measure ranges between -4 and 4. No dimension 'dominates' SOCDIV: each dimension has nearly the same loading (between 0.45 and 0.54). This reflects the previously mentioned strong positive correlation among the four variables contributing to SOCDIV. SOCDIV appears therefore an adequate summary of the overall social divisiveness in a given country.[5]

We include in our baseline model time-varying control variables which are usually seen as potential determinants of social conflicts (Sambanis, 2002; Fearon and Laitin, 2003; Collier and Hoeffler, 2004; Dixon, 2009): log of income per capita (GDPPC), natural resources abundance (NATRES) and political civil liberties (POLCIV). In doing so, we mirror the empirical models usually found in the empirical studies of conflict (e.g. Table 1 of Ray and Esteban (2017)). The main difference between those models and ours is the absence of time-invariant variables given that we control for country fixed effects in our baseline model. In Section 3.3., we will examine the effects of other and less consensual factors, related to income inequality, demography, or education.

Income per capita can be seen as a measure of opportunity cost of engaging into social conflict or an indicator of state institutional capacity to defuse violent conflict. In both cases, the coefficient on income per capita ought to be negative. Real income per capita, expressed in 2011 US dollars, comes from The Maddison Project Database.[6]

[4] See James et al. (2017) for an excellent introduction to principal components analysis.

[5] We show in various sections of the paper that our results are not driven by one single dimension.

[6] `https://www.rug.nl/ggdc/historicaldevelopment/maddison/`

Natural resources may trigger a social conflict if some groups wish to appropriate a larger share of the revenues they generate. These groups may be predatory and motivated by pure looting but a sentiment of unfair redistribution of the natural resources rent may also motivate their actions. In parallel, a state benefiting from abundant natural resources may be able to finance the expenditures required to repress insurrections or appease popular dissatisfaction but may also suffer from a lack of state capacity. The role played by natural resources in triggering social conflicts is therefore ambiguous. Natural resources abundance corresponds to total resource income (the volume of production of oil, gas, coal, metals times the price of these resources) per capita, expressed in 2007 US dollars, and transformed using an inverse hypberbolic sine transformation (to deal with outliers and zero values). Data were constructed by Haber and Menaldo (2011).

Political repression can lead to the escalation of social conflicts as a major channel of peaceful expression is cut off. At the same time, the ability of the state to repress this voice channel may increase the costs of group coordination. The impact of this variable is thus unclear. For consistency, the index of political civil liberties come from V-Dem, ranges from 0 to 1, and is an aggregation of various indicators related to freedom of association and freedom of expression.

Summary statistics for our (unbalanced) panel dataset are provided in Table 1. Values for standard deviations or min-max ranges show that our sample includes countries with very different characteristics. Such a strong variation ought to facilitate the econometric identification of effects.

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2.3 Stylised facts

In this Section, we provide some stylised facts. Figure 2 shows that social divisiveness and anti-system opposition are positively correlated, although high values of SOCDIV are not necessarily associated with high values of ANTISYS. This dispersion of points

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
ANTISYS	-0.293	1.335	-3.104	3.964
SOCDIV	0.000	1.662	-3.983	4.300
PARTGOODS	-0.403	1.266	-3.230	3.114
CIVSOC	-0.344	1.313	-3.174	2.937
CIVCINC	-0.593	1.270	-3.377	2.476
CIVREG	-0.184	1.313	-2.664	2.884
GDPPC	8.582	1.198	5.626	12.907
NATRES	4.123	2.856	0.000	11.635
POLCIV	0.529	0.331	0.012	0.986

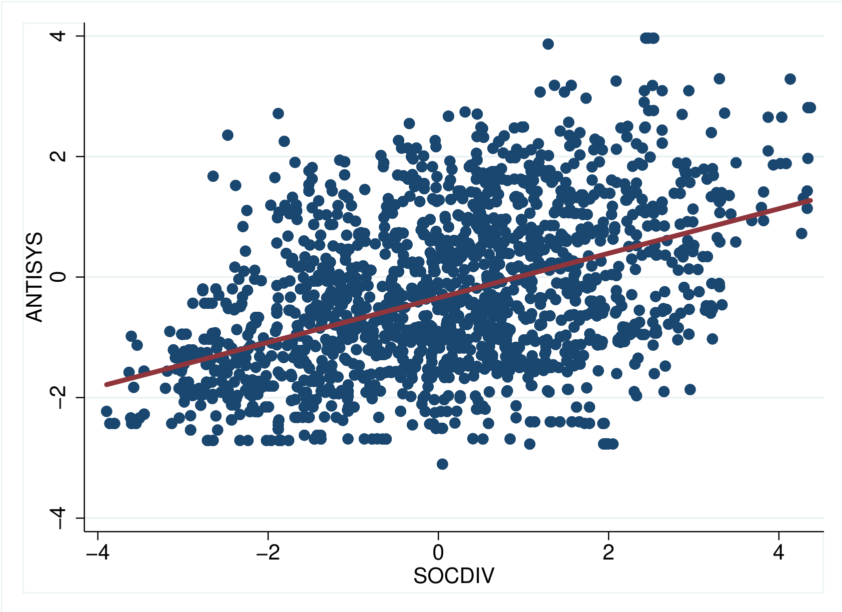
is reassuring as it suggests that the V-dem experts have not assumed that high social divisiveness automatically leads to high anti-system opposition. Figure 3 reports binned scatterplots. These are a non-parametric method of plotting the conditional expectation function: SOCDIV values have been grouped into twenty equal-sized bins and the means of SOCDIV and ANTISYS have been computed within each bin. In presence of a large number of observations, binned scatterplots clarify how two variables are associated. We can see, even after adjusting for country and time fixed effects, that there is a strong positive linear relationship between SOCDIV and ANTISYS.

Figure 4 indicates that regions drastically differ in both social divisiveness and anti-system opposition. From a cross-regional perspective, LAC, and, to a lower extent SSA and MENA, are characterised by higher SOCDIV and ANTISYS than other regions. From a time-series perspective, both social divisiveness and anti-system opposition have globally fallen over the 1945-2000 period. Nevertheless, in more recent decades, there is a rise in anti-system opposition, notably in the MENA region.

Figure 5 highlights that our ANTISYS measures captures a broad spectrum of anti-system manifestations: violent and non-violent, low-intensity and high-intensity. The ANTISYS values are higher when there is a civil war, high levels of (predominantly violent) social unrest, or an ongoing non-violent campaign.

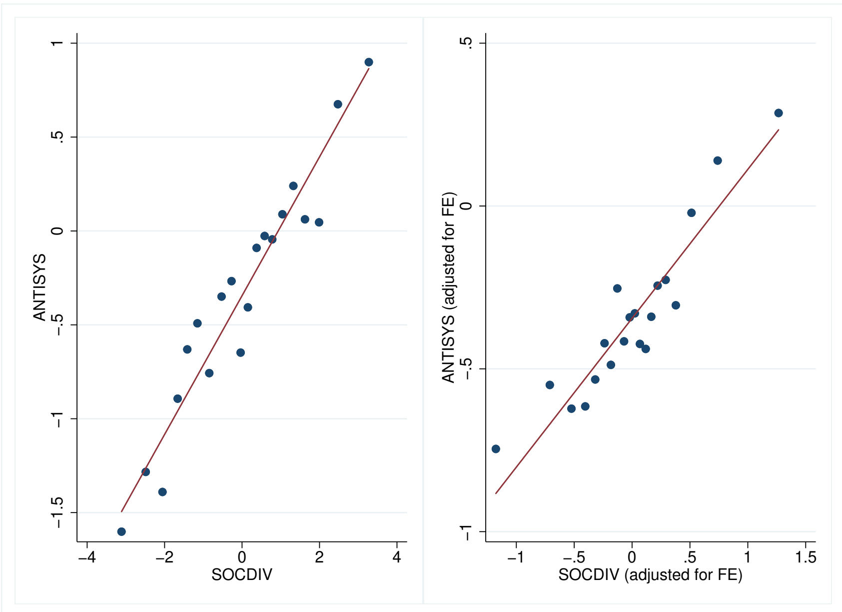
Figure 6 underlines a positive relationship between SOCDIV and time-invariant measures of ethnic polarisation and ethnic fractionalisation, suggesting that the latter may be

Figure 2: Unconditional relationship between anti-system opposition (ANTISYS) and social divisiveness (SOCDIV)



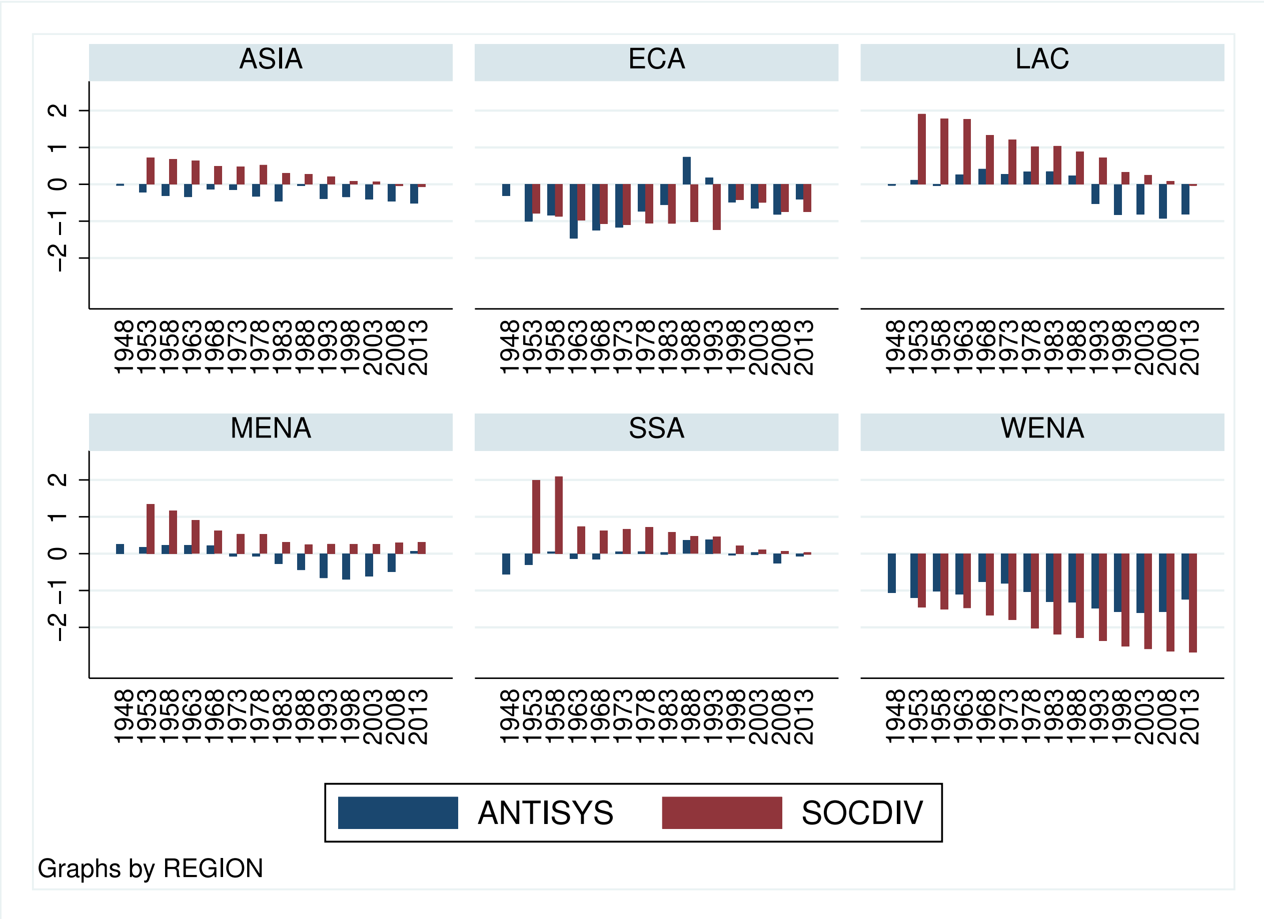
Notes: five-year periods over 1946-2015. Slope: 0.369 (statistically significant at the 1% level). SOCDIV lagged by one period.

Figure 3: Binned scatterplots of ANTISYS against SOCDIV



Notes: five-year periods over 1946-2015. SOCDIV values have been grouped into twenty equal-sized bins and the means of SOCDIV and ANTISYS have been computed within each bin. The regression line is the same as in Figure 2. Values have been adjusted for the presence of country and time fixed effects in the right hand-side panel. SOCDIV lagged by one period.

Figure 4: ANTISYS and SOCDIV, by region



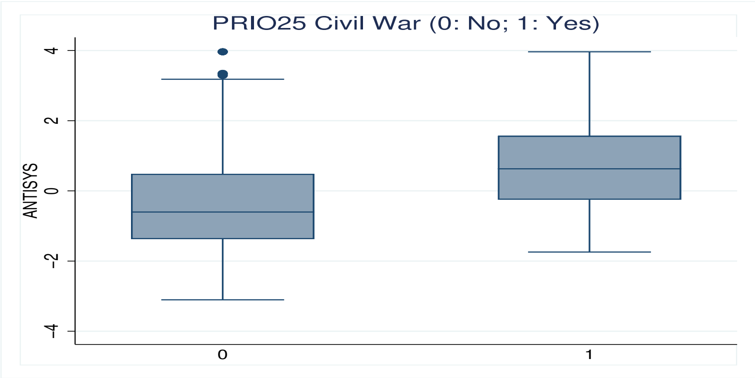
Notes: five-year periods over 1946-2015. SOCDIV lagged by one period. Regions according to World Bank classification. ASIA: East Asia and Pacific + South Asia. ECA: Eastern Europe and Central Asia. LAC: Latin America and Carribean. MENA: Middle East and North Africa. SSA: Sub Saharan Africa. WENA: Western Europe and North America.

some of the deep determinants of the former. However, SOCDIV varies over time and points are spread around the fit line. Hence, ethnic divisions are unlikely to be the sole determinants of social divisiveness.

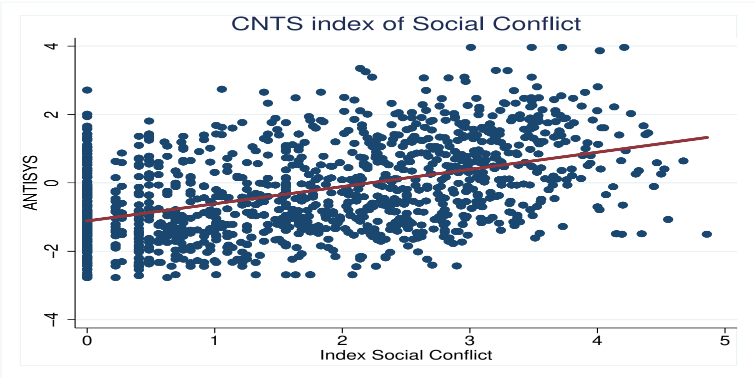
Figure 7 shows the historical experience of a selected number of countries through the lens of our ANTISYS and SOCDIV indicators. Values of ANTISYS and SOCDIV clearly vary between and within countries. Focusing first on ANTISYS, we can retrace the growing popular discontent in Egypt (Revolution in 2011), the heavy repression of the Ben Ali regime in Tunisia (post-1989), the end of Apartheid in South Africa (1994), the recurrent political instability in Bolivia, the relative improvement of the political situation in the Philippines following the end of the Marcos era (post-1985), or the efforts in the United Kingdom to address demands for greater redistribution and regional autonomy (post-1998). Turning now to SOCDIV (lagged by one period), its evolution tends to mirror that of ANTISYS. Its various dimensions also tend to move together, although one or two specific dimensions may, at a given point of time, drive changes in SOCDIV. Public goods particularism (PARTGOODS) and Social class inequality (CIVINC) appear to be common shifters of social divisiveness across countries. These country-specific examples show that our ANTISYS and SOCDIV indicators capture key political events and various sources of grievances.

We end this section with a brief case study. The literature on horizontal inequalities has contrasted the historical experiences of Ghana and Ivory Coast (Stewart, 2008). These two countries are perceived to have similar socio-economic characteristics. Both Ghana and Ivory Coast notably host a large variety of ethnic groups, different religious affiliations, and large North-South regional economic disparities. However, their social trajectories, as reflected by the ANTISYS and SOCDIV indicators plotted in Figure 8, have been drastically different. From around 1983, both social conflict and social divisiveness have drastically fallen in Ghana whereas the opposite is true for Ivory Coast. Langer (2008) attributes these divergences to the distinct policies pursued by the State. On the one hand,

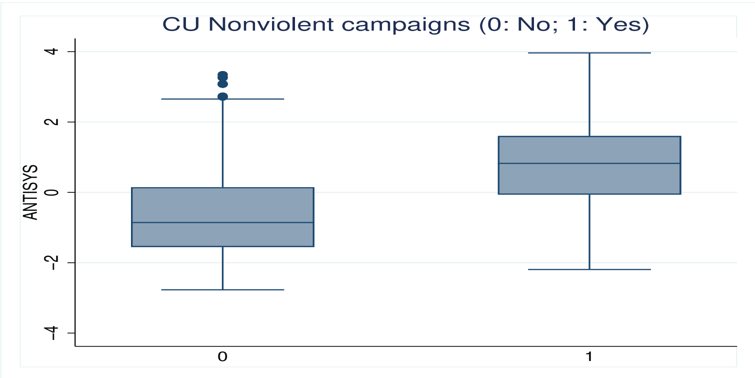
Figure 5: ANTISYS and various measures of social conflicts



Notes: Five-year periods over 1961-2010. Data from Esteban et al. (2012) and originally from the UCDP/PRIO dataset: a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths per year and per incompatibility. Five-year periods over 1960-2010.

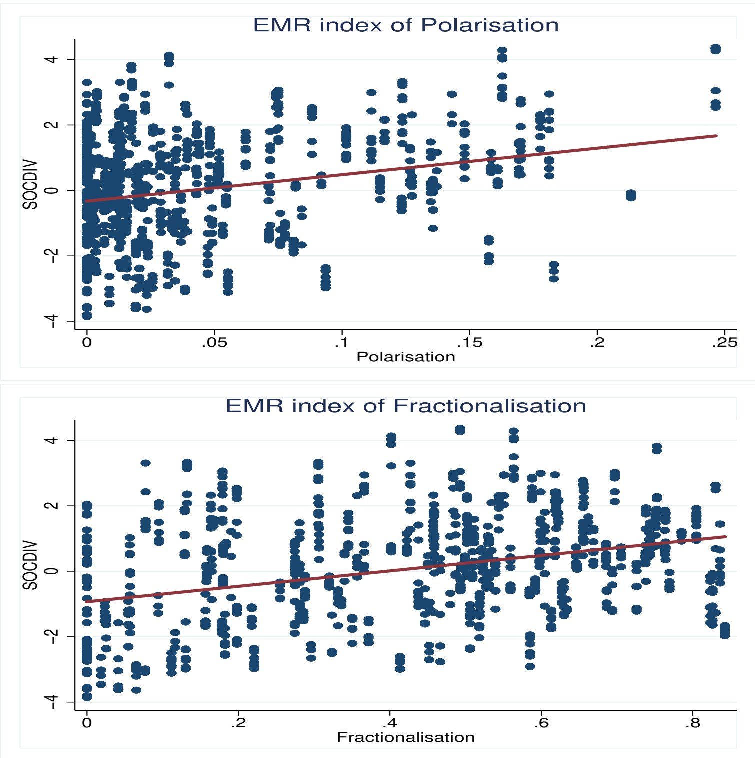


Notes: Five-year periods over 1961-2010. Data from Esteban et al. (2012) and originally from the Cross-National Time-Series Data Archive (CNTS): weighted average [...] of eight variables (Assassinations [25]; General Strikes [20]; Guerrilla Warfare [100]; Major Government Crises [20]; Purges [20]; Riots [25]; Revolutions [150]; Antigovernment Demonstrations [10]).



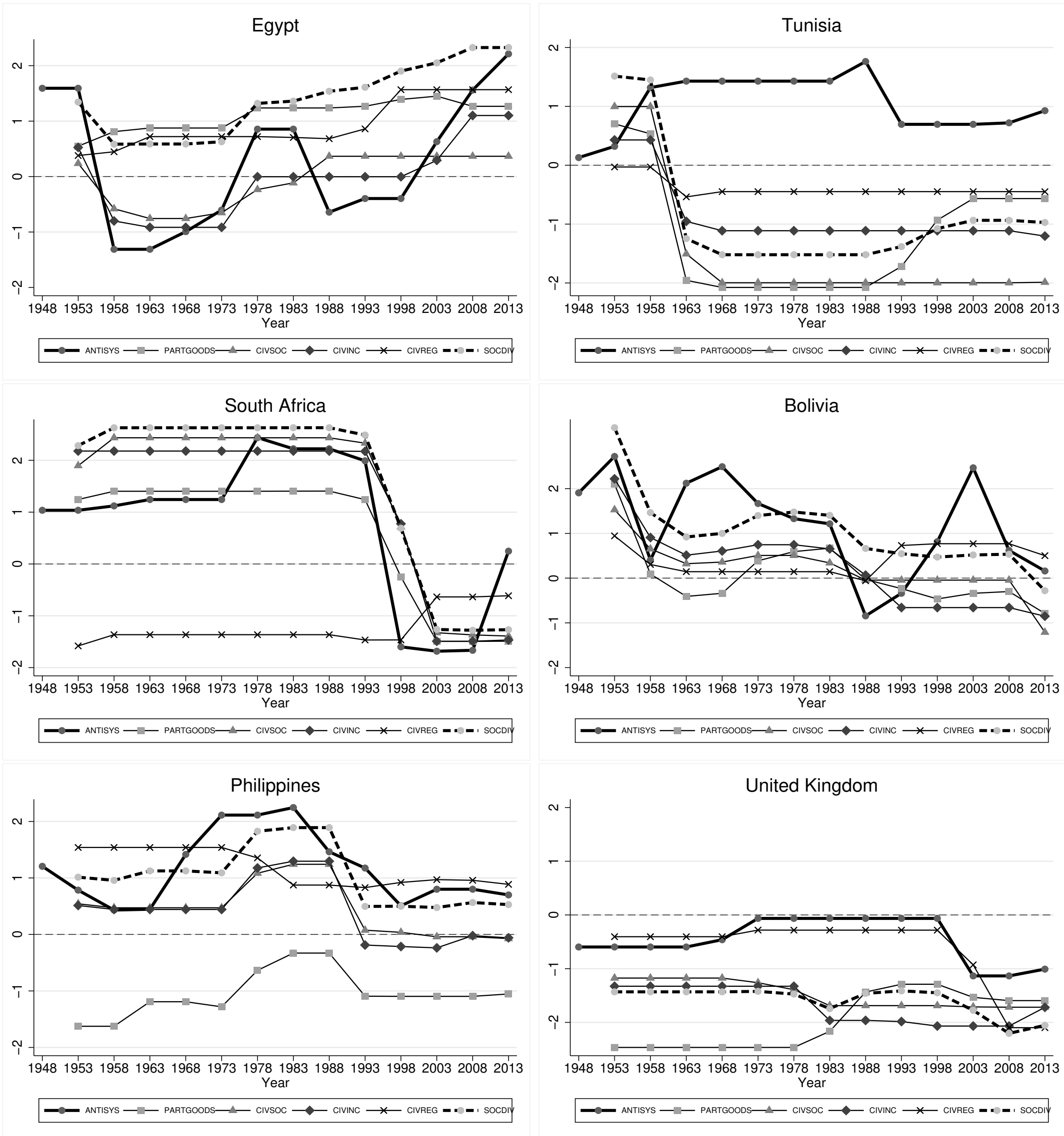
Notes: Five-year periods over 1951-2010. Data from Chenoweth and Ulfelder (2017). A nonviolent campaign is a mass and coordinated event involving at least 1000 people, with the pursuit of a maximalist goal (e.g. removal of the incumbent government), and without making use of violence. Boxplot: the box is defined by the 25^{th}, 50^{th} and 75^{th} percentiles. More extreme values are indicated by the adjacent lines (which can extend two-thirds the width of a box).

Figure 6: SOCDIV and ethnic divisions



Notes: Five-year periods over 1961-2010. Data come from Esteban et al. (2012) [EMR]. The measures are calculated using the sizes of ethnic groups in a given country and (for polarisation) their linguistic distances. SOCDIV lagged by one period.

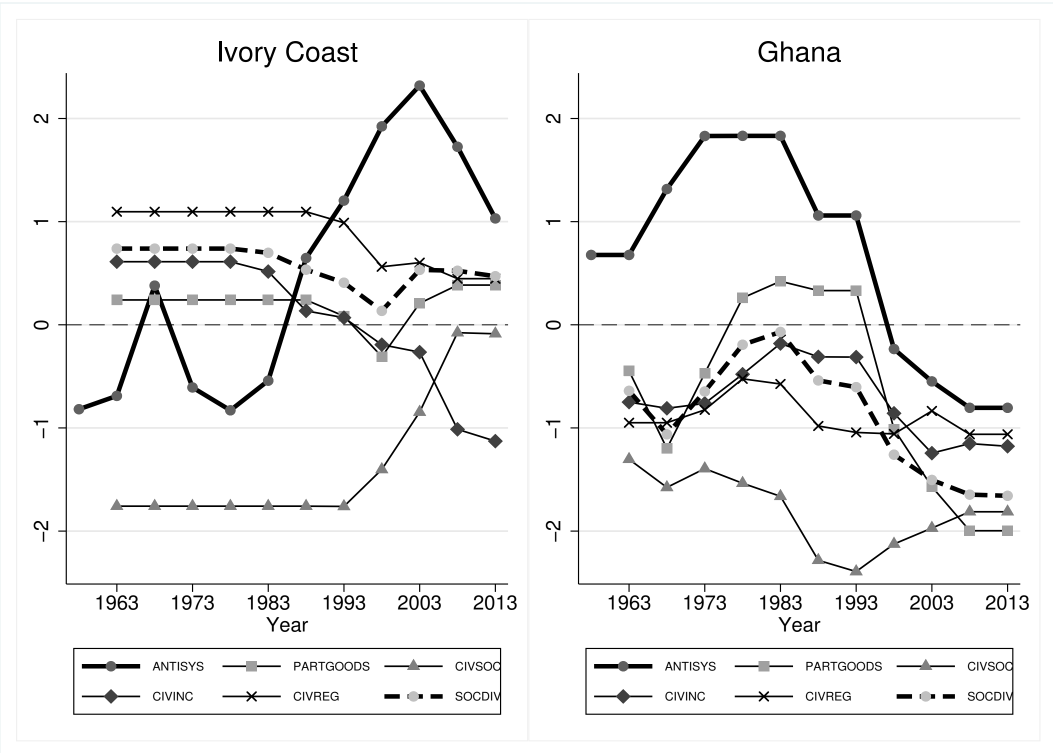
Figure 7: ANTISYS and SOCDIV components, selected countries



Notes: Five-year periods over 1946-2015. SOCDIV and its components are lagged by one period.

In Ivory Coast, an informal system of ethnic quotas within the main state institutions have been progressively abandoned and, in parallel, specific ethnic groups, religions, and regions have been increasingly favoured. On the other hand, in Ghana, consecutive regimes have tried to address the regional economic divide and promote national integration over time. The formation of political parties along ethnic, religious, or regional lines are formally banned, political ethno-regional balance is a recurrent objective, and cultural and religious inclusiveness is actively promoted. Beyond showing again the alignment of our ANTISYS and SOCDIV indicators with country-specific histories, this tale of two countries highlights that ethno-religious diversity does not irremediably lead to social conflict when the social divisiveness that diversity may generate is contained or defused.

Figure 8: The diverging social trajectories of two African countries



Notes: Five-year periods over 1946-2015. SOCDIV and its components are lagged by one period.

3 Results

3.1 Initial results

We present our initial results in Table 2. In columns (1) to (4), we investigate, in turn, the impacts of particularistic spending (PARTGOODS), social group inequality (CIVSOC), social class inequality (CIVINC), and subnational civil liberties unevenness (CIVREG) on the level of anti-system movement activity (ANTISYS). In each case, the estimated coefficient is large, positive, and statistically significant, indicating that higher inequality of treatment is associated with greater opposition to the current political system. Column (5) shows that, when including together, each dimension of social divisiveness, besides CIVSOC (possibly because of its high correlation with CIVINC, as shown in Figure 1), has an independent statistically significant effect on ANTISYS. In column (6), we use our overall measure of social divisiveness (SOCDIV). The coefficient on SOCDIV is large, positive, and statistically significant.[7] The practical implication is substantial. A one standard deviation in SOCDIV would increase ANTISYS by a 0.62 standard deviation. For comparison the beta coefficient for GDPPC is -0.26.[8] In column (7), instead of using the maximum level of anti-system movement activity during a given period, we use the average level. This leaves our results unchanged. Turning to our control variables, only the coefficient on income per capita is statistically significant. Anti-system opposition tends to fall when economic growth (measured here as mean-deviations given the presence of country fixed effects) is strong in the previous period. A negative association between income per capita and civil war is a standard result in the literature (Ray and Esteban, 2017).

[7] We show in the Appendix that the variables (PARTGOODS, CIVSOC, CIVINC, CIVREG) combined in the first principal component do not seem to have further explanatory power once the latter (SOCDIV) is included in the regression since their coefficients are small and not statistically significant.

[8] Alternatively, moving from the average values in the first quartile (-2.46; e.g. France in the period 2006-2010) to average values in the last quartile (1.24, e.g. Syria in the period 2006-2010) of SOCDIV would increase anti-system opposition by 1.85.

Table 2: Social divisiveness and anti-system opposition

	Anti-system opposition (ANTISYS)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PARTGOODS L.1	0.365***				0.232***		
	(0.080)				(0.078)		
CIVSOC L.1		0.321***			0.061		
		(0.109)			(0.104)		
CIVINC L.1			0.452***		0.258**		
			(0.109)		(0.110)		
CIVREG L.1				0.303***	0.199**		
				(0.092)	(0.091)		
Social divisiveness (SOCDIV L.1)						0.500***	0.486***
						(0.080)	(0.074)
GDPPC L.1	-0.328**	-0.349**	-0.368***	-0.329**	-0.297**	-0.295**	-0.260**
	(0.140)	(0.142)	(0.138)	(0.140)	(0.134)	(0.135)	(0.123)
NATRES L.1	0.052	0.052	0.055	0.053	0.044	0.043	0.036
	(0.034)	(0.036)	(0.035)	(0.034)	(0.033)	(0.034)	(0.031)
POLCIV L.1	0.073	0.246	0.183	-0.109	0.312	0.422	0.435
	(0.290)	(0.349)	(0.287)	(0.310)	(0.300)	(0.289)	(0.268)
Observations	1,615	1,615	1,615	1,615	1,615	1,615	1,615

Notes: ***, **, *, denote a significance level of 1, 5, and 10 percent. Cluster-robust standard errors are in parentheses. L.1: first lag. Country and time fixed effects are included.

3.2 Robustness checks and extensions

3.2.1 Measurement uncertainty

ANTISYS and SOCDIV are subjective measures based on the assessments of multiple country experts. The V-Dem measurement model explicitly acknowledges that the experts can diverge in their opinions, mental scales of analysis, or reliability. The point estimates generated thus come with measures of their uncertainty. Following Desbordes and Koop (2016), we adopt a multiple imputation approach to take into account the fact that our key variables are measured with uncertainty. In broad terms, we estimate the models presented in Table 2 200 different times, drawing each time different values of ANTISYS and SOCDIV from their (assumed to be normal) distributions, and we take the average of these 200 estimates. Table 3 shows that we still find that social divisiveness is a positive and statistically significant determinant of anti-system opposition. The main difference with our previous results is a fall in the magnitude of our estimated impacts. For example, the coefficient on SOCDIV in column (4) of Table 3 is about 50% smaller than its counterpart in Table 2. This may reflect the presence in our dataset of debatable and outlying events, combining potentially high social divisiveness, notably in terms of social group inequality, and high anti-system opposition.

Table 3: MI approach to uncertainty around ANTISYS and SOCDIV

	Anti-system opposition (ANTISYS)					
	(1)	(2)	(3)	(4)	(5)	(6)
PARTGOODS L.1	0.284***					
	(0.077)					
CIVSOC L.1		0.204**				
		(0.095)				
CIVINC L.1			0.288***			
			(0.096)			
CIVREG L.1				0.528***		
				(0.077)		
Social divisiveness (SOCDIV L.1)					0.283***	0.277***
					(0.072)	(0.066)
GDPPC L.1	-0.272**	-0.271**	-0.283**	-0.250**	-0.236**	-0.207**
	(0.108)	(0.111)	(0.116)	(0.106)	(0.108)	(0.100)
NATRES L.1	0.067*	0.073**	0.069*	0.059*	0.066*	0.059*
	(0.034)	(0.035)	(0.036)	(0.034)	(0.035)	(0.032)
POLCIV L.1	-0.325	-0.283	-0.245	-0.424	-0.179	-0.012
	(0.260)	(0.261)	(0.311)	(0.277)	(0.269)	(0.251)
Observations	1,615	1,615	1,615	1,615	1,615	1,615

Notes: ***, **, *, denote a significance level of 1, 5, and 10 percent. Cluster-robust standard errors are in parentheses. L.1: first lag. Country and time fixed effects are included. MI: multiple imputations (200).

3.2.2 Dynamics, cross-region heterogeneity, spatial effects

In Table 4, we allow for the possibility of dynamics, cross-region heterogeneity, and spatial effects. In column (1), we include a lagged dependent variable to allow for the possibility that social responses to changes in inequality of treatment takes time to occur. This variable may also control for omitted time-varying variables. Given the nature of our dynamic panel data model (small T and large N), we use the quasi-maximum likelihood estimator developed by Hsiao et al. (2002). We find a statistically significant and positive short-run impact of social divisiveness, which is about four times smaller than its long-run impact ($\frac{0.118}{1-0.738} = 0.45$). This long-run estimate is very close to that found in the static model estimated in column (6) of Table 2. As shown by Baltagi and Griffin (1984) and Egger and Pfaffermayr (2005), when the current value of a regressor is strongly correlated with its past values and dynamic adjustment is slow -as in our case, the static fixed effects estimator tends to converge towards the long-run effect. In column (2), we control for country-specific time trends. Our results are unchanged.

Table 4: Robustness checks and extensions

	Anti-system opposition (ANTISYS)					
	Dynamic model (1)	Country-sp. trends (2)	Between-Within model (3)	Regional interactions (4)	Regional time effects (5)	Spatial model (6)
Social divisiveness (SOCDIV L.1)	0.118***	0.470***			0.444***	0.551***
	(0.043)	(0.103)			(0.087)	(0.088)
ANTISYS L.1	0.738***					
	(0.046)					
(B)etween_SOCDIV L.1			0.281***	0.350***		
			(0.057)	(0.106)		
B_SOCDIV L.1*ASIA				0.153		
				(0.158)		
B_SOCDIV L.1*LAC				-0.093		
				(0.137)		
B_SOCDIV L.1*MENA				-0.308		
				(0.226)		
B_SOCDIV L.1*SSA				-0.070		
				(0.152)		
(W)ithin_SOCDIV L.1			0.500***	0.338***		
			(0.080)	(0.124)		
W_SOCDIV L.1*ASIA				-0.195		
				(0.239)		
W_SOCDIV L.1*LAC				0.423**		
				(0.182)		
W_SOCDIV L.1*MENA				0.188		
				(0.188)		
W_SOCDIV L.1*SSA				0.199		
				(0.190)		
ANTISYS spatial (inverse) distance-weighted						0.157
						(0.182)
Observations	1,440	1,615	1,615	1,615	1,615	1,034

Notes: ***, **, *, denote a significance level of 1, 5, and 10 percent. Cluster-robust standard errors are in parentheses. L.1: first lag. Country fixed effects, time fixed effects, and control variables are included in all regressions (GDPPC, NATRES, CIVPOL). Region dummy variables are included in columns (4)-(5). Regions according to World Bank classification. ASIA: East Asia and Pacific + South Asia. ECA: Eastern Europe and Central Asia. LAC: Latin America and Carribean. MENA: Middle East and North Africa. SSA: Sub Saharan Africa. WENA: Western Europe and North America; omitted category.

In column (3), we estimate a 'within-between' model, in which we model anti-system movement activity as a function of differences in the average values of our variables across countries and in changes in the values of our variables over time within countries (Bell and Jones, 2015; Desbordes et al., 2018). Given that the changes are expressed as mean-deviations, coefficients on these components are the same as those estimated in column (6) of Table 2 (Mundlak, 1978). Such a decomposition is useful for three reasons. From an economic perspective, we expect the level of social divisiveness to influence anti-system opposition not only over time but across space. From an econometric perspective, we can examine whether our results hold when we rely on an alternative, and, orthogonal source of identification, i.e. the cross-sectional variation instead of the time-series variation. A strong divergence of results could imply that our measure of social divisiveness is correlated with time-invariant unobserved factors but also that, in fact, the dynamic effects are much more complex than what we presume. Finally, looking at the impact of the average values of social divisiveness makes our results more comparable with those of studies whose analysis is based on time-invariant proxies for the latency of social conflict (e.g. ethnic fractionalisation/polarisation).

The coefficient on cross-sectional averages of social divisiveness is positive, statistically significant, with a magnitude smaller than the coefficient on mean-deviations. It is possible that changes in SOCDIV have a larger impact than average levels of SOCDIV because a process of habituation, well documented in the life satisfaction literature (Clark et al., 2008), takes place. Individuals adapt to favorable or unfavorable circumstances, implying that the intensity of emotional responses to changes in the statu quo falls over time.

This being said, column (4), where the two components of social divisiveness are interacted with regional dummy variables, shows that this difference in magnitude is driven by countries located in Latin America and the Caribbean (LAC). In these countries the effect of a change in social divisiveness is more than twice as large as in the rest of the world. For other regions, we cannot reject that the responses over time and across regions are the same, positive, and statistically significant. We also observe that the 'base' cross-sectional and time-series estimates are very close to each other (and their difference is statistically insignificant). Overall, these results indicate that the positive impact of social divisiveness on anti-system opposition is a long-lasting relationship, not specific to a particular group of countries.

In the last columns of Table 4, we investigate the presence of localised spatial effects. Lawson (2015) argues that demonstrations in other 'Arab' countries may have led to a regional wave of uprisings in the MENA region. While our time fixed effects pick up shocks influencing all countries in a given year, they cannot control for time-varying regional factors. Hence, in column (5), we include interactions between the period dummy variables and the regional dummy variables. This has little impact on the coefficient on social divisiveness suggesting that changes in anti-system movement activity are driven by country-specific conditions. In column (6), we examine explicitly whether events in other countries can have an independent influence in a given country. We estimate a spatial (autoregressive) model which includes the (inverse) distance-weighted value of the opposition to current political system in neighbouring countries. Estimation is done by Maximum Likelihood (Elhorst, 2014).[9] Again, we fail to find evidence that anti-system opposition is influenced by anti-system opposition in neighbouring countries.

3.3 Income inequality, natural resources, demography, and education

The literature has suggested other potential determinants of anti-system opposition. Inter-individual income inequality (sometimes described as 'vertical inequality') has often been put forward, notably by Political Science researchers, as a key factor driving social conflict (Cramer, 2003). However, empirical evidence is extremely mixed (Ray and Esteban, 2017). In Table 5, we initially exclude SOCDIV and we include a measure of net inter-individual income inequality (INCINEQ), taken from the Standardized World Income Inequality Database [SWIID] (Solt, 2016). SWIID provides the largest and most consistent cross-country coverage of gross and net inter-individual income inequality; we still lose about half of our observations, often those associated to developing countries. The correlation coefficient between SOCDIV and INCINEQ is 0.55, statistically significant at the 1% level. Both variables may proxy for the same factor. Social divisiveness may also partly determine inter-individual income inequality.

[9] The Maximum Likelihood estimator is based on the maximisation of a likelihood function which includes a correction to deal with the endogeneity issue created by the existence of spatial effects (feedback effects). This correction differentiates the Maximum Likelihood estimator from the OLS estimator. The estimator requires a balanced panel. For this reason, we restrict our panel to the period 1955-2015 to maximise the number of observations.

Column (1) shows that the coefficient on INCINEQ is positive but small and not statistically significant.[10] On the other hand, in column (2), when we include again SOCDIV, we find an impact of social divisiveness on anti-system opposition very similar to that found using the full sample. Taken together, our results suggest that inter-group (horizontal) income inequality is likely to be a more important determinant of anti-system opposition than inter-individual (vertical) income inequality. These results echo those of Cederman et al. (2013), who find that inter-group income inequality, but not inter-individual income, increases the probability of civil war onset. Nevertheless, we acknowledge that the relationship between income inequality and social conflict is complex and requires a much more granular analysis than the one carried out in this paper. In this regard, Ray and Esteban (2017) provide an excellent discussion of the various theoretical mechanisms through which income inequality, but also somehow paradoxically economic similarity, may generate social conflict.

In columns (3) and (4) we explore whether resources abundance (measured either by total resource income per capita, NATRES, or total oil income per capita, OILRES) does not exacerbate the effects of social divisiveness. This could be the case if the resource rents are perceived to be unequally redistributed. However, in both columns, the coefficients on the interaction terms are small and statistically insignificant.[11]

In columns (5) and (6), following Campante and Chor (2014) we examine, through additional interaction terms, whether anti-system opposition is not larger when a large fraction of the population is either young (% of 15-24 people in total population; YOUTH) or well-educated (years of secondary schooling in the population aged 25 and above; EDUC) and economic opportunities (proxied by income per capita; GDPPC) are scarce. Weak economic prospects may generate dissatisfaction, notably in those who have invested in

[10]Similar results when we use both cross-sectional and time-series variations for identification, through the estimation of a random effects model.

[11]We also fail to find any statistically significant impact whezn we interact SOCDIV with a dummy variable (from `https://wp.nyu.edu/dri/resources/global-development-network-growth-database/`) taking the value of one when the country is primarily an exporter of fuels.

Table 5: Interactions and other explanations

	Anti-system opposition (ANTISYS)					
	(1)	(2)	(3)	(4)	(5)	(6)
Social divisiveness (SOCDIV L.1)		0.452***	0.488***	0.501***	0.546***	0.563***
		(0.109)	(0.115)	(0.092)	(0.079)	(0.086)
INCINEQ L.1	0.107	-1.685				
	(2.193)	(2.297)				
NATRES L.1	-0.025	-0.049	0.042		0.036	0.031
	(0.038)	(0.037)	(0.033)		(0.034)	(0.039)
NATRES*SOCDIV L.1			0.002			
			(0.014)			
OILRES L.1				0.051		
				(0.031)		
OILRES*SOCDIV L.1				0.007		
				(0.011)		
GDPPC L.1	-0.090	0.068	-0.300**	-0.302**	-0.041	-0.408**
	(0.260)	(0.276)	(0.137)	(0.129)	(0.293)	(0.164)
YOUTH L.1					13.292	
					(12.963)	
YOUTH*GDPPC L.1					-1.360	
					(1.344)	
EDUC L.1						-0.150
						(0.690)
EDUC*GDPPC L.1						0.026
						(0.061)
CIVPOL L.1	-0.860***	-0.165	0.420	0.439	0.377	0.412
	(0.293)	(0.322)	(0.290)	(0.294)	(0.279)	(0.291)
Observations	846	846	1,615	1,592	1,499	1,339

Notes: ***, **, *, denote a significance level of 1, 5, and 10 percent. Cluster-robust standard errors are in parentheses. L.1: first lag. Country and time fixed effects are included.

their human capital and/or attempt to find their 'first' job. Nevertheless, coefficients on the new interaction terms are not statistically significant.[12]

Across all regressions, the coefficients on SOCDIV are large, positive, and statistically significant.

3.4 Violent conflicts and ethnic divisions

Our results may be purely driven by the occurrence of violent conflicts in some countries. We investigate this possibility in column (1) of Table 6. We include in our model current and lagged (by one period) measures of international violence (INTVIOL)/war (INTWAR), civil violence (CIVVIOL)/war (CIVWAR), ethnic violence (ETHVIOL)/war (ETHWAR); data come from the Center for Systemic Peace (Major Episodes of Political Violence), episodes are rated on a 0 (no episode) to 10 (highest level of violence/war) scale, and 'war' is defined as a higher intensity event than 'violence'.[13] In that way, we 'purge' our dependent and explanatory variables from the effects of the most violent forms of anti-system opposition. As expected, we observe that increasingly more violent domestic (but not international) conflicts are associated with greater levels of opposition to the current political system. In itself, this is a reassuring result regarding the validity of our dependent variable. Furthermore, relative to our previous results, the coefficient on SOCDIV is virtually unchanged. This suggests that our dependent variable captures the full spectrum of anti-system activity, violent and non-violent, and that the effects of inequality of treatment are not necessarily channeled through violent uprisings.

The work of Esteban et al. (2012) is related to ours. In addition to ethnic fractionalisation, they highlight the importance of ethnic polarisation as a determinant of high-intensity social conflict. Drawing on Esteban and Ray (2011)'s theoretical model, they convincingly argue that this result shows the importance of disputes over public goods

[12] Data on population and education come from Nations (2017) and Barro and Lee (2013), respectively. Similar results are found when we use the change in income per capita as component of the interaction terms.

[13] `http://www.systemicpeace.org/inscr/MEPVcodebook2016.pdf`

Table 6: Violent conflicts, ethnic divisions, and social divisiveness

	ANTISYS	PRIO25	PRIO25	PRIO25	ANTISYS
	OLS	LOGIT	LOGIT	LOGIT	OLS
	(1)	(2)	(3)	(4)	(5)
Polarisation		6.499***	3.264	3.140	2.492
		(2.284)	(2.564)	(2.599)	(1.755)
Fractionalisation		1.254**	1.490***	1.495***	0.374
		(0.538)	(0.541)	(0.542)	(0.483)
Greenberg-Gini index		-5.090*	-4.771*	-4.755*	0.152
		(2.849)	(2.660)	(2.651)	(0.556)
SOCDIV L.1	0.483***		0.409***		
	(0.081)		(0.077)		
Between_SOCDIV L.1				0.422***	
				(0.083)	
Within_SOCDIV L.1				0.345**	
				(0.163)	
INTERVIOL	0.176				
	(0.115)				
INTERVIOL L.1	0.059				
	(0.122)				
INTERWAR	-0.016				
	(0.044)				
INTERWAR L.1	0.011				
	(0.058)				
CIVVIOL	0.374***				
	(0.130)				
CIVVIOL L.1	-0.045				
	(0.073)				
CIVWAR	0.294***				
	(0.055)				
CIVWAR L.1	-0.021				
	(0.031)				
ETHVIOL	0.160				
	(0.126)				
ETHVIOL L.1	-0.024				
	(0.113)				
ETHWAR	0.199***				
	(0.044)				
ETHWAR L.1	-0.129***				
	(0.044)				
Observations	1,584	1,013	1,013	1,013	1,197

Notes: ***, **, *, denote a significance level of 1, 5, and 10 percent. Cluster-robust standard errors are in parentheses. PRIO25: a conflict with at least 25 or more battle deaths in a given subperiod. L.1: first lag. Country fixed effects are included in column (1). Time fixed effects are included in columns (1) and (5). Control variables are included in all regressions. For columns (1) and (5), the control variables are GDPPC, NATRES, CIVPOL. In the case of columns (2)-(4), these are log population, log GDP per capita, a dummy variable for oil/diamond production, percentage of mountainous terrain, non-contiguity of country territory, and democracy.

broadly defined (e.g. access to economic resources, political and civil rights, cultural dominance) in conflict determination. We would then expect, that a key channel linking ethnic polarisation and civil war incidence is social divisiveness. We examine the validity of this causal chain of effects in columns (2)-(4) of Table 6. In column (2), we estimate the econometric model of Esteban et al. (2012), using their original data and on a sample for which also have data on SOCDIV. Our results are extremely similar to their original estimates. In column (3), we include SOCDIV. The coefficient on ethnic polarisation becomes much smaller and is no more statistically significant once we control for SOCDIV, whose coefficient is large, positive, and statistically significant. On the other hand, the coefficients on the other two distributional measures (ethnic fractionalisation and the population-scaled Gini-Greenberg index) are little affected. In column (4), we obtain similar findings when we decompose social decisiveness into its cross-country (averages) and time-series (mean-deviations) components. Coefficients on both components are positive, large, statistically significant, and very similar. Taken together, these results suggest that greater ethnic polarisation is associated with more social conflict because some groups are willing to take decisive actions to be treated in a better way. This confirms Esteban et al. (2012)'s interpretation, but also comforts us in the conceptual validity of our measure of social divisiveness.

In column (5), we test whether Esteban et al. (2012)'s distributional measures can explain differences in the value of our indicator of anti-system activity; social divisiveness is excluded. Their coefficients are relatively large and have the expected signs, but they are not statistically significant. This is possibly because, unlike social divisiveness, these measures cannot capture the full spectrum of degrees in inequality of treatment. We explore this hypothesis in Section 3.6.

3.5 The potential endogeneity of social divisiveness

In our econometric model, all explanatory variables are lagged by one period because we believe that their effects take time to operate. However, except under specific conditions, using a lagged explanatory variable does not solve endogeneity issues related to an unobserved confounding variable or simultaneity (Bellemare et al., 2017). To deal with the potential endogeneity of SOCDIV, we adopt various instrumental variables (IV) approaches in Table 7.

Table 7: Correcting for the potential endogeneity of SOCDIV

VARIABLES	SOCDIV	ANTISYS	SOCDIV	ANTISYS	ANTISYS	ANTISYS	ANTISYS
	OLS (1)	GMM-2S (2)	OLS (3)	GMM-2S (4)	DIFF-GMM (5)	SYS-GMM (6)	SYS-GMM (7)
SOCDIV L.1		0.365**		0.452***	0.262**	0.276***	0.170**
		(0.167)		(0.136)	(0.117)	(0.071)	(0.073)
ANTISYS L.1					0.703***	0.788***	0.741***
					(0.052)	(0.031)	(0.041)
Polarisation	9.410***		9.340***				
	(2.011)		(2.003)				
SOCDIV L.1.D.1.			0.057				
			(0.082)				
SOCDIV L.2.D.1.			0.362***				
			(0.079)				
GDDPC L.1	-0.510***	-0.234*	-0.514***	-0.172	0.030	0.031	-0.158**
	(0.099)	(0.121)	(0.100)	(0.106)	(0.076)	(0.045)	(0.068)
NATRES L.1	0.036	-0.001	0.037	-0.007	0.018	0.000	0.005
	(0.040)	(0.035)	(0.040)	(0.035)	(0.017)	(0.011)	(0.024)
CIVPOL L.1	-2.079***	0.330	-1.982***	0.460	0.228	0.498***	-0.040
	(0.322)	(0.494)	(0.334)	(0.448)	(0.184)	(0.167)	(0.345)
Nb. IV		1		3	47	60	97
First-stage F-statistic		21.90		16.94			
Autocorr. test p-value		0.432		0.432	0.204	0.222	0.164
Overid. restr. test p-value				0.345	0.589	0.376	0.401
Observations	1,085	1,085	1,085	1,085	1,462	1,615	1,615

Notes: ***, **, *, denote a significance level of 1, 5, and 10 percent. Cluster-robust standard errors are in parentheses. L.1: first lag. D.1: first difference. Time fixed effects are included in all regressions. Columns (2) and (4): two-step efficient generalised method of moments (GMM-2S) estimator. Columns (5)-(7): orthogonal deviations transform is used and instrument count is reduced using principal component analysis.

We exploit the fact that ethnic polarisation is likely to be a deep and exogenous determinant of SOCDIV.[14] We therefore use the former as an instrument for the latter. The

[14] Esteban et al. (2012) provide various robustness checks to demonstrate the exogeneity of their distributional measures.

first-stage results are in column (1).[15] Ethnic fractionalisation has a positive, large, and statistically significant impact on SOCDIV. Notably, an increase in ethnic polarisation of 0.10 would increase SOCDIV by about one point. Column (2) shows the second-stage results. The coefficient on SOCDIV is positive, statistically significant, with a magnitude close to our previous estimates.

In columns (3) and (4), in order to both capture part of the time variation of SOCDIV and run a test for the exogeneity of the instruments, we use as additional IV the first and second lags of the first differences of SOCDIV. As long as there is no autocorrelation of the error term, these 'internal' instruments ought to be valid. In column (3), the coefficient on ethnic polarisation remains positive, large, and statistically significant, and the coefficient on the second lag of the first difference of SOCDIV is positive, large and statistically significant. In column (4), we still find that SOCDIV seems to have a causal effect on ANTISYS. Furthermore, our specifications tests indicate that the instrument is relevant (F-statistic above 10) and valid (p-value of the overidentifying restrictions test above 0.10; p-value of the test for serial correlation of the error term above 0.10).

It is extremely common in the literature (see Van der Weide and Milanovic (2018) for a recent example) to deal with the potential endogeneity of some variables by estimating dynamic panel data models using 'DIFF-GMM' (Arellano and Bond, 1991) and 'SYS-GMM' estimators (Arellano and Bover, 1995; Blundell and Bond, 1998). In very broad terms, for the 'DIFF-GMM' estimator, fixed effects are first removed by applying a suitable transformation (e.g. differencing or orthogonal deviations) and then lags (usually lags 2 and up) of the untransformed troublesome variables are used as IV.[16] The SYS-GMM estimator combines this estimation in differences with an estimation in levels where lags of the differences of the troublesome variables (usually lag 1 and up) are used

[15]The estimated models in columns (1)-(4) do not include country fixed effects because ethnic polarisation is time-invariant.

[16]In columns (5)-(7) of Table 7, we use the orthogonal deviations transformation. It is a transformation very close to the within transformation (which facilitates the comparison of results), it maximises the number of observations in an unbalanced panel, and a 'DIFF-GMM' estimator based on orthogonal deviations has been shown to perform better than one based on the first difference (Hayakawa, 2009).

as IV. These ‘internal’ instruments ought to be valid as long as the error term is not serially correlated. Both estimators have advantages and drawbacks (Roodman, 2009): the ‘SYS-GMM’ estimator may perform better than the ‘DIFF-GMM’ estimator if the variables are highly persistent but the former requires additional assumptions. For this reason, we use each estimator in columns (5) and (6). Both the first lag of ANTISYS and SOCDIV are treated as endogenous and instrumented with their (appropriately transformed) lagged values.[17] Results are very similar in columns (5) and (6) and the diagnostic tests indicate that our instruments are valid. The coefficients on SOCDIV are positive and statistically significant with a short-run effect much smaller than the long-run impact (about 0.26-0.28 vs. 0.88-1.30). Finally, in column (7), we apply again the SYS-GMM estimator but treat all explanatory variables as potentially endogenous. We now find a short-run effect of SOCDIV of 0.17, a long-run effect of SOCDIV of 0.66, and a negative impact of income per capita on opposition to the current political regime; the other explanatory variables are not statistically significant.

Overall, our previous results do not appear to have been driven by any endogeneity biases.

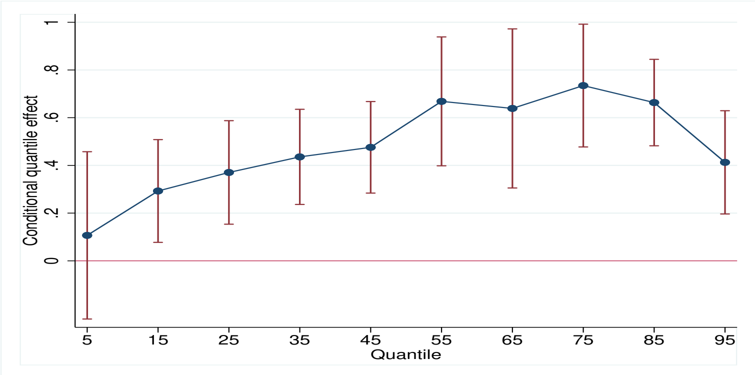
3.6 Quantile effects

In this last section, we investigate whether the effects of social divisiveness are the same across the distribution of anti-system opposition. We expect social divisiveness to influence substantially more high levels (quantiles) of anti-system opposition than low levels (quantiles) of anti-system opposition. Inequality of treatment is likely to be a salient source of social contention, with discriminated groups attempting to modify political institutions in fundamental ways to alter the status quo in their favour. To explore this idea, we estimate a between-within quantile regression model (Wooldridge, 2010) and we focus

[17]To avoid an overfitting bias, we apply principal components analysis to the‘GMM’-style instruments. In that way, we produce a smaller instrument set that is maximally representative of the original (Mehrhoff, 2009).

on the within estimates. Figure 9 reports the estimated effects of a rise in social divisiveness at various conditional quantiles of anti-system opposition. Two observations can be made. First, our results appear to be robust to outliers given that the conditional median effect is close to the conditional average effect we previously estimated. Second, while the various quantile effects are estimated with a relatively large degree of uncertainty, we observe nevertheless as hypothesised that the effect of a rise in social divisiveness is statistically significant for most quantiles, positive, and stronger in the higher quantiles of anti-system opposition. Figure 10 highlights that findings are very similar when we replace, in turn, SOCDIV by its dimensions.

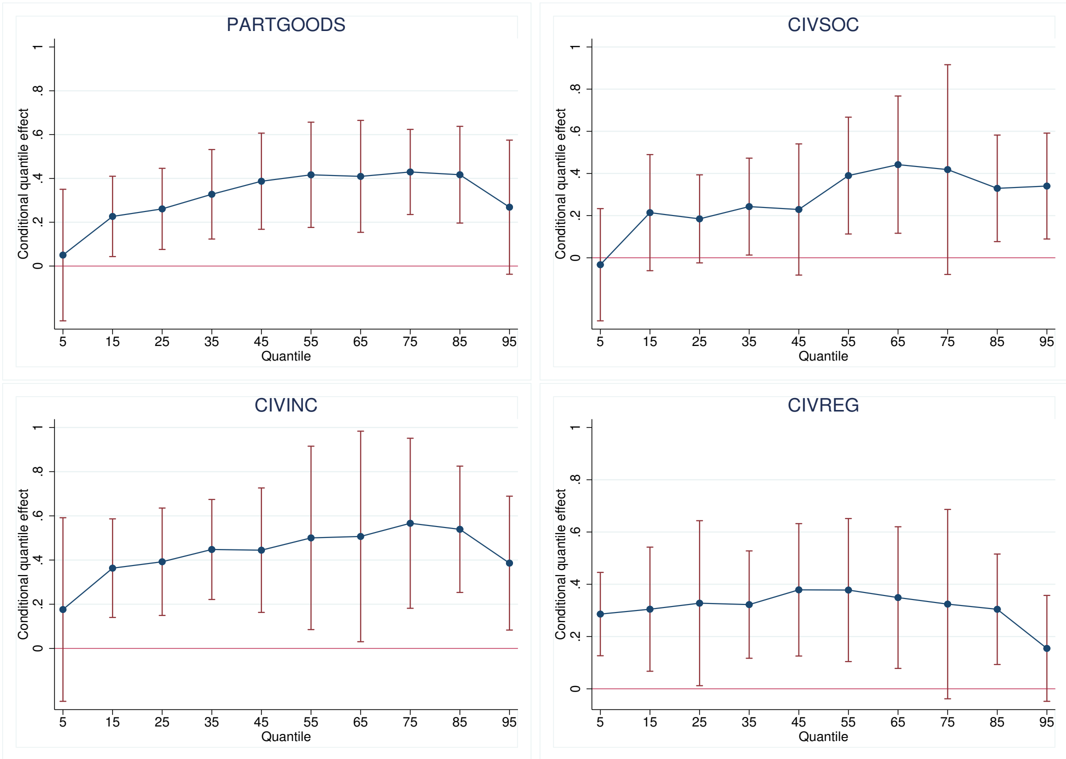
Figure 9: Conditional quantile effects of SOCDIV on ANTISYS



Notes: Between-within quantile regression model, within estimates plotted. Cluster-robust standard errors. Capped spikes denote a 95% confidence interval. Time fixed effects and control variables (GDPPC, NATRES, CIVPOL) are included.

We do the same exercise but with the distributional measures of Esteban et al. (2012) using here a pooled approach given that these measures are time-invariant. Figure 11 shows that, relative to our previous results, ethnic polarisation has a statistically significant effect on anti-system opposition but only at the 95^{th} quantile of anti-system opposition. Higher ethnic polarisation increases the level of the most intense anti-system movements but has little effect on lower levels of anti-system activity. Such a result suggests that groups suffering from the consequences of ethnic polarisation believe that their grievance can solely be addressed, when action is taken, through a drastic change in the political system. This explains why ethnic polarisation is such a strong determinant of civil armed

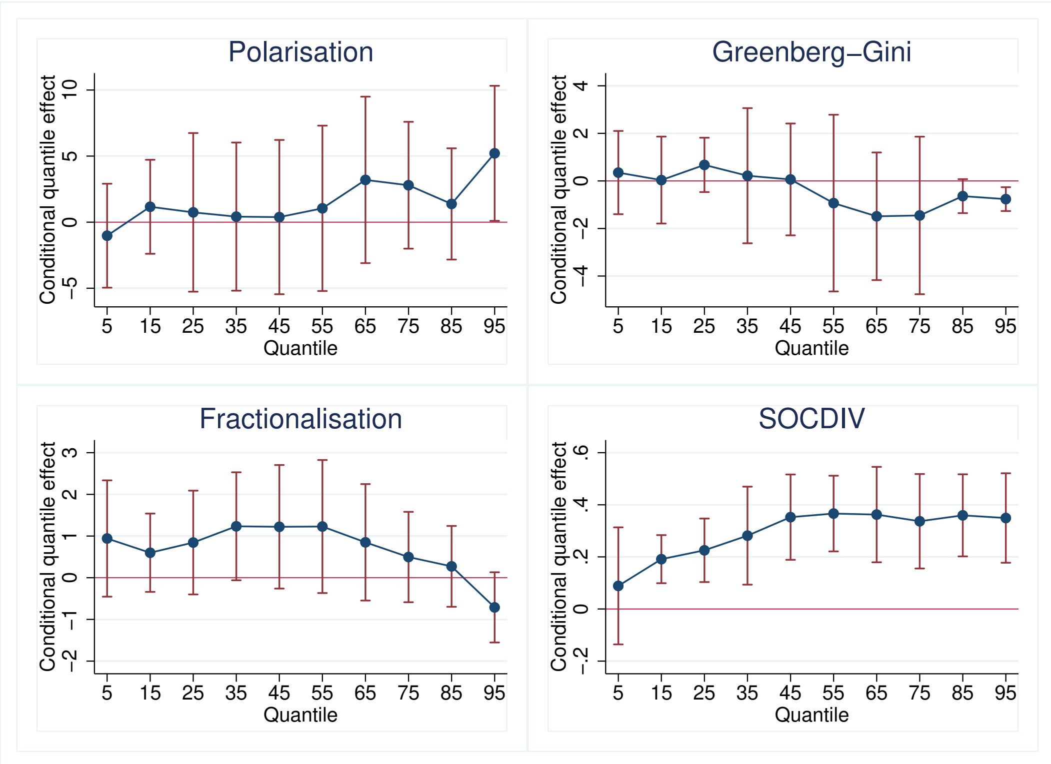
Figure 10: Conditional quantile effects of SOCDIV components on ANTISYS



Notes: Between-within quantile regression model, within estimates plotted. Cluster-robust standard errors. Capped spikes denote a 95% confidence interval. Time fixed effects and control variables (GDPPC, NATRES, CIVPOL) are included.

conflict, a violent and relatively rare occurrence of anti-system activity. On the other hand, ethnic polarisation is a poor determinant of overall anti-system movement because it mostly captures a very specific dimension of social divisiveness. In other words, not all social divisiveness is the product of this time-invariant structural characteristic and therefore not all social conflicts are driven by ethnic divisions. For instance, in column (1) of Table 7, ethnic polarisation explains about 14% of the variation in SOCDIV, controlling for other covariates.

Figure 11: Conditional quantile effects of ethnic divisions on ANTISYS



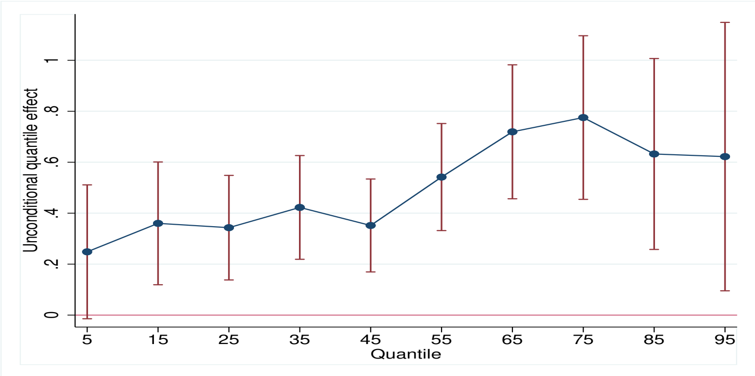
Notes: Pooled quantile regression model. Cluster-robust standard errors. Capped spikes denote a 95% confidence interval. Time fixed effects and control variables (log population, log GDP per capita, a dummy variable for oil/diamond production, percentage of mountainous terrain, non-contiguity of country territory, and democracy) are included.

For comparison, in the last right-bottom panel of Figure 11, we plot the quantile effects of social divisiveness, using the same (pooled) econometric model. As in Figure 9, we find that the effect of social divisiveness is large, positive, and statistically significant across quantiles, with a larger magnitude as the conditional quantile increases. Higher social divisiveness can explain a rise in opposition to the current political system at all levels because some of its aspects can be dealt within the current political system, without necessarily requiring to abandon the latter.

We have so far looked at the effects of social divisiveness on the conditional quantiles of anti-system opposition, i.e. quantiles adjusted for differences in the values of the other covariates. We may also be interested in investigating the effects of social divisiveness on the unconditional quantiles of anti-system oppostion, still controlling for other explanatory variables. Differences in these two approaches can be understood by thinking about the dual meaning of OLS estimates. They can either be interpreted as the effect of a given variable on the conditional mean of an outcome or, by the law of iterated expectations, on the unconditional mean of this outcome regardless of the other explanatory variables included in the model. Conditional quantile regressions provide conditional marginal effects and unconditional quantile regressions provide unconditional marginal effects (Firpo et al., 2009; Maclean et al., 2014). From a policy perspective, estimation of this latter effect is important because we can assess, for example, whether reducing social divisiveness in some countries would reduce their observed (and not their conditional) level of anti-system opposition, especially if opposition to the current political system is currently very strong.

Figure 12 reports the estimated effects of social divisiveness on the unconditional quantiles of anti-system opposition using the (fixed effects) recentered influence function (RIF) approach proposed by (Firpo et al., 2009). In practice, Figure 9 and Figure 12 are very similar, possibly because other explanatory variables do not have much explanatory power. Policies addressing social divisiveness would reduce social conflicts in all countries, with an especially large impact on countries currently experiencing high levels of anti-system opposition.

Figure 12: Uncondtional quantile effects of SOCDIV on ANTISYS



Notes: Unconditional quantile regression model. Cluster-robust standard errors. Capped spikes denote a 95% confidence interval. Country fixed effects, time fixed effects and control variables (GDPPC, NATRES, CIVPOL) are included.

4 Conclusion

We have demonstrated in this paper that there is a strong link between social divisiveness and social conflicts worldwide. The obvious policy implication is that actions ought to be taken to reduce group inequalities (Stewart, 2008). Policies can be direct (e.g. specific policies targeting deprived groups), indirect (e.g. general policies promoting power sharing and forbidding discrimination), or integrationist (e.g. cross-group policies reducing the salience of group identities). The stakes involved are high. Apart from issues of social justice (Stewart, 2014), high social divisiveness is likely to be associated with weak economic development, with one potentially feeding the other (Alesina and Ferrara, 2005; Alesina et al., 2016). Grievances, and their alleviation, thus matter for a harmonious and prosperous society.

References

Alesina, Alberto and Ferrara, Eliana La (2005) 'Ethnic Diversity and Economic Performance', *Journal of economic literature*, Vol. 43, pp. 762–800.

Alesina, Alberto, Michalopoulos, Stelios, and Papaioannou, Elias (2016) 'Ethnic Inequality', *Journal of Political Economy*, Vol. 124, pp. 428–488.

Arampatzi, Efstratia, Burger, Martijn, Ianchovichina, Elena, Röhricht, Tina, and Veenhoven, Ruut (2018) 'Unhappy Development: Dissatisfaction With Life on the Eve of the Arab Spring', *Review of Income and Wealth*, Vol. 64, pp. 80–113.

Arellano, Manuel and Bond, Stephen (1991) 'Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations', *Review of Economic Studies*, Vol. 58, pp. 277–97.

Arellano, Manuel and Bover, Olympia (1995) 'Another Look at the Instrumental Variable Estimation of Error-Components Models', *Journal of Econometrics*, Vol. 68, pp. 29–51.

Baltagi, B. H. and Griffin, J. M. (1984) 'Short and Long Run Effects in Pooled Models', *International Economic Review*, Vol. 25, pp. 631–645.

Barro, Robert J and Lee, Jong Wha (2013) 'A New Dataset of Educational Attainment in the World, 1950-2010', *Journal of development economics*, Vol. 104, pp. 184–198.

Bell, Andrew and Jones, Kelvyn (2015) 'Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data', *Political Science Research and Methods*, Vol. 3, pp. 133–153.

Bellemare, Marc F, Masaki, Takaaki, and Pepinsky, Thomas B (2017) 'Lagged Explanatory Variables and the Estimation of Causal Effect', *The Journal of Politics*, Vol. 79, pp. 949–963.

Blattman, Christopher and Miguel, Edward (2010) ‘Civil war’, *Journal of Economic literature*, Vol. 48, pp. 3–57.

Blundell, Richard and Bond, Stephen (1998) ‘Initial Conditions and Moment Restrictions in Dynamic Panel Data Models’, *Journal of Econometrics*, Vol. 87, pp. 115–143.

Campante, Filipe R and Chor, Davin (2014) ‘The People Want the Fall of the Regime: Schooling, Political Protest, and the Economy’, *Journal of Comparative Economics*, Vol. 42, pp. 495–517.

Cederman, Lars-Erik, Gleditsch, Kristian Skrede, and Buhaug, Halvard (2013) *Inequality, Grievances, and Civil War*: New York: Cambridge University Press.

Chenoweth, Erica, Stephan, Maria J, and Stephan, Maria J (2011) *Why Civil Resistance Works: The Strategic Logic of Nonviolent Conflict*: New York: Columbia University Press.

Chenoweth, Erica and Ulfelder, Jay (2017) ‘Can Structural Conditions Explain the Onset of Nonviolent Uprisings?’, *Journal of Conflict Resolution*, Vol. 61, pp. 298–324.

Clark, Andrew E, Frijters, Paul, and Shields, Michael A (2008) ‘Relative Income, Happiness, and Utility: An Explanation For the Easterlin Paradox and Other Puzzles’, *Journal of Economic literature*, Vol. 46, pp. 95–144.

Collier, Paul and Hoeffler, Anke (2004) ‘Greed and Grievance in Civil War’, *Oxford economic papers*, Vol. 56, pp. 563–i595.

Collier, Paul, Hoeffler, Anke, and Rohner, Dominic (2009) ‘Beyond Greed and Grievance: Feasibility and Civil War’, *Oxford Economic papers*, Vol. 61, pp. 1–27.

Cramer, Christopher (2003) ‘Does Inequality Cause Conflict?’, *Journal of International Development*, Vol. 15, pp. 397–412.

Dalacoura, Katerina (2012) ‘The 2011 Uprisings in the Arab Middle East: Political Change and Geopolitical Implications’, *International Affairs*, Vol. 88, pp. 63–79.

Desbordes, Rodolphe and Koop, Gary (2016) ‘Should We Care About the Uncertainty Around Measures of Political-Economic Development?’, *Journal of Comparative Economics*, Vol. 44, pp. 752–763.

Desbordes, Rodolphe, Koop, Gary, and Vicard, Vincent (2018) ‘One Size Does Not Fit All… Panel Data: Bayesian Model Averaging and Data Poolability’, *Economic Modelling*, Vol. 75, pp. 364–376.

Devarajan, Shantayanan and Ianchovichina, Elena (2017) ‘A Broken Social Contract, Not High Inequality, Led to the Arab Spring’, *Review of Income and Wealth*, Vol. 64, pp. 5–25.

Dixon, Jeffrey (2009) ‘What Causes Civil Wars? Integrating Quantitative Research Findings’, *International Studies Review*, Vol. 11, pp. 707–735.

Egger, P. and Pfaffermayr, M. (2005) ‘Estimating Long and Short Run effects in Static Panel Models’, *Econometric Reviews*, Vol. 23, pp. 199–214.

Elhorst, Paul J. (2014) *Spatial Econometrics. From Cross-Sectional Data to Spatial Panels*: London: Springer.

Esteban, Joan, Mayoral, Laura, and Ray, Debraj (2012) ‘Ethnicity and Conflict: An Empirical Study’, *American Economic Review*, Vol. 102, pp. 1310–42.

Esteban, Joan and Ray, Debraj (2011) ‘Linking Conflict to Inequality and Polarization’, *American Economic Review*, Vol. 101, pp. 1345–74.

Fearon, James D and Laitin, David D (2003) ‘Ethnicity, Insurgency, and Civil War’, *American political science review*, Vol. 97, pp. 75–90.

Firpo, Sergio, Fortin, Nicole M, and Lemieux, Thomas (2009) ‘Unconditional Quantile Regressions’, *Econometrica*, Vol. 77, pp. 953–973.

Goodwin, Jeff (2011) ‘Why We Were Surprised (Again) by the Arab Spring’, *Swiss Political Science Review*, Vol. 17, pp. 452–456.

Haber, Stephen and Menaldo, Victor (2011) 'Do Natural Resources Fuel Authoritarianism? A Reappraisal of the Resource Curse', *American political science Review*, Vol. 105, pp. 1–26.

Hayakawa, Kazuhiko (2009) 'First Difference or Forward Orthogonal Deviation. Which Transformation Should Be Used in Dynamic Panel data Models?: A Simulation Study', *Economics Bulletin*, Vol. 29, pp. 2008–2017.

Hsiao, Cheng, Pesaran, M Hashem, and Tahmiscioglu, A Kamil (2002) 'Maximum Likelihood Estimation of Fixed Effects Dynamic Panel Data Models Covering Short Time Periods', *Journal of econometrics*, Vol. 109, pp. 107–150.

James, Gareth, Witten, Daniela, Hastie, Trevor, and Tibshirani, Robert (2017) *An Introduction to Statistical Learning*: New York: Springer, eigth edition.

Langer, Arnim (2008) 'When Do Horizontal Inequalities Lead to Conflict? Lessons From a Comparative Study of Ghana and Côte d'Ivoire', in Frances Stwart ed. *Horizontal Inequalities and Conflict: Understanding Group Violence in Multiethnic Societies*: New York: Palgrave Macmillan, pp. 163–189.

Lawson, George (2015) 'Revolution, Nonviolence, and the Arab Uprisings', *Mobilization: An International Quarterly*, Vol. 20, pp. 453–470.

Maclean, Johanna Catherine, Webber, Douglas A, and Marti, Joachim (2014) 'An Application of Unconditional Quantile Regression to Cigarette Taxes', *Journal of Policy Analysis and management*, Vol. 33, pp. 188–210.

Mehrhoff, Jens (2009) 'A Solution to the Problem of Too Many Instruments in Dynamic Panel Data GMM', mimeo.

Mundlak, Yair (1978) 'On the Pooling of Time Series and Cross Section Data', *Econometrica*, Vol. 46, pp. 69–85.

Nations, United (2017) *World Population Prospects. The 2017 Revision*: New York: United Nations, Department of Economic and Social Affairs.

Østby, Gudrun (2008) 'Polarization, Horizontal Inequalities and Violent Civil Conflict', *Journal of Peace Research*, Vol. 45, pp. 143–162.

Ray, Debraj and Esteban, Joan (2017) 'Conflict and Development', *Annual Review of Economics*, Vol. 9, pp. 263–293.

Roodman, David (2009) 'A Note on the Theme of Too Many Instruments', *Oxford Bulletin of Economics and Statistics*, Vol. 71, pp. 135–158.

Sambanis, Nicholas (2002) 'A Review of Recent Advances and Future Directions in the Quantitative Literature on Civil War', *Defence and Peace Economics*, Vol. 13, pp. 215–243.

Schock, Kurt (2013) 'The Practice and Study of Civil Resistance', *Journal of Peace Research*, Vol. 50, pp. 277–290.

Solt, Frederick (2016) 'The Standardized World Income Inequality Database', *Social science quarterly*, Vol. 97, pp. 1267–1281.

Stewart, Frances (2008) *Horizontal Inequalities and Conflict: Understanding Group Violence in Multiethnic Societies*: New York: Palgrave Macmillan.

——— (2014) 'Why Horizontal Inequalities are Important for a Shared Society', *Development*, Vol. 57, pp. 46–54.

Thurber, Ches (2018) 'Ethnic Barriers to Civil Resistance', *Journal of Global Security Studies*, Vol. 3, pp. 255–270.

Van der Weide, Roy and Milanovic, Branko (2018) 'Inequality Is Bad For Growth of the Poor (But Not For That of the Rich)', *The World Bank Economic Review*, Vol. 32, pp. 507–530.

Wooldridge, Jeffrey M. (2010) *Econometric Analysis of Cross Section and Panel Data*: Cambridge, MA: The MIT Press, second edition.

Appendix

Table 8: Testing for residual explanatory power

	Anti-system opposition (ANTISYS)			
	(1)	(2)	(3)	(4)
PARTGOODS L.1	0.066			
	(0.101)			
CIVSOC L.1		-0.171		
		(0.127)		
CIVINC L.1			0.044	
			(0.146)	
CIVREG L.1				0.021
				(0.108)
Social divisiveness (SOCDIV L.1)	0.445***	0.596***	0.470***	0.490***
	(0.111)	(0.108)	(0.123)	(0.101)
GDPPC L.1	-0.294**	-0.296**	-0.298**	-0.293**
	(0.136)	(0.135)	(0.134)	(0.135)
NATRES L.1	0.043	0.044	0.043	0.042
	(0.034)	(0.033)	(0.034)	(0.034)
CIVPOL L.1	0.401	0.311	0.421	0.415
	(0.284)	(0.301)	(0.290)	(0.290)
Observations	1,615	1,615	1,615	1,615

Notes: ***, **, *, denote a significance level of 1, 5, and 10 percent. Cluster-robust standard errors are in parentheses. L.1: first lag. Country and time fixed effects are included.