Introducing the Anatomy of Resistance Campaigns (ARC) Dataset*

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Abstract

We introduce the Anatomy of Resistance Campaigns (ARC) dataset, which records information on 1,426 organizations that participated in events of maximalist violent and nonviolent contention in Africa from 1990-2015. The ARC data contain 18 variables covering organization-level features such as type, age, leadership, goals and inter-organizational alliances. These data facilitate new measurements of key concepts in the study of contentious politics, such as the social and ideological diversity of resistance episodes, in addition to measures of network centralization and fragmentation. The ARC dataset helps resolve existing debates in the field and opens new avenues of inquiry.

Keywords: organizations, networks, protest, dissent, civil war, data

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Most resistance movements are comprised of organizations that mobilize people, make tactical decisions, issue demands, and accept or reject concessions (Haggard & Kaufman, 2016; Metternich et al., 2013; Braithwaite & Cunningham, 2020; Cunningham et al., 2017; McAdam, 2010; Tarrow, 2011). Organizations often head transitional regimes, assume power after post-conflict elections, and re-mobilize when democratic institutions are threatened (Haggard & Kaufman, 2016; Wood, 2000). However, we lack systematic cross-national data on dissident organizations spanning a variety of tactics, goals, and group identities.

This matters because organizational dynamics are often central to theories of the onset, dynamics, and outcomes of violent and nonviolent resistance campaigns (Bethke & Pinckney, 2019; Brancati, 2016; Chenoweth & Stephan, 2011; Celestino & Gleditsch, 2013; Huang, 2016; Schaftenaar, 2017; Thurber, 2019; Sutton et al., 2014; Svensson & Lindgren, 2011; Belgioioso, 2018). Empirical analyses, however, usually depend on broad indicators of contention summarized over a campaign or campaign-year (Chenoweth & Stephan, 2011), which leaves uncertainty around whether the theorized mechanisms drive observed effects (Schock, 2005). Case studies show that resistance campaigns involve complex networks of organizations and social groups (Metternich et al., 2013; Schock, 2005; Osa, 2003) and demonstrate – with detailed assessments of actors and their characteristics – that the features of these organizations and networks help explain tactical choices, campaign outcomes, and democratization (Pearlman, 2011; Thurber, 2019; Nepstad, 2011; Schock, 2005; Wood, 2000; Collier, 1999). Yet, it is difficult to generalize these findings to a larger sample of cases.

The Anatomy of Resistance Campaigns (ARC) dataset provides information on 1,426 distinct organizations across 3,407 organization-country-years associated with events of 'maximalist' collective dissent in Africa from 1990-2015. ARC includes information on organization types, origins, leadership, mobilization bases, goals, network ties, relationships with the state, and more. These data enable detailed observations of actor- and network-level characteristics across a large sample of cases, allowing scholars to unpack the organizational composition of resistance campaigns and their network structures. The ARC data can help answer lingering questions: how do ideological diversity and unity (through fronts and alliances) impact campaign outcomes and post-conflict institutional change (Chenoweth & Stephan, 2011; Bayer et al., 2016; Celestino & Gleditsch, 2013)? Are some campaigns more resilient to repression than others because of their network structures or the nature of participating organizations (Sutton et al., 2014; Siegel, 2009)? How do coalitions evolve through periods of institutional reform – especially democratic transitions (Pinckney, 2020)? To the extent that data availability shapes theoretical horizons (Gleditsch et al., 2014), ARC can stimulate additional research questions in myriad areas.

Core concepts in ARC

The ARC dataset focuses on *organizations* that participated in acts of *collective dissent* for goals of *maximalist* change. *Organizations* are structures designed to cohere people and resources - often through collective action - to pursue common goals (North, 1990; Daft, 1992: 2). The presence of a formal structure (however thin the hierarchy) intended to aggregate individual efforts towards a defined goal distinguishes organizations from broad social categories such as "students," "protesters," or the "working class." We discuss our operationalization of this concept in a subsequent section.

Collective dissent is observable action involving multiple people, beyond normal institutional procedures for realizing political goals (Tilly, 1978). This ranges from demonstrations and strikes to rebellion and terrorist attacks, while excluding actions lacking a clear political goal and everyday or institutional political activities such as lobbying politicians or electoral participation. Organizations engage in collective dissent when they deploy their mobilization infrastructure to encourage individual participation in these events.

We define *maximalist* demands as calls for changes in the political structure that would significantly alter the executive's access to state power, the rules with which executives are selected, or the policy or geographic areas for which the executive has the right to make laws. Examples of maximalism include demands that a head of state resign via a non-institutional method, for democratization in autocratic settings, to enfranchise an excluded social group, and for regional or ethnic autonomy or independence.[1] Maximalist demands exclude calls that fall short of altering these fundamental aspects of executive power, such as improved human rights protections or changes in public spending. Demands by a disenfranchised group for better protections can be addressed with legislation that typically does not change the process for deciding who holds executive power or who has lawmaking authority. Demands for enfranchisement of that excluded group are maximalist because – if implemented – they would include a new group in the process of deciding who holds executive power.

Relationship to existing datasets

ARC is distinct from existing resources because it provides information on the features of organizations that participated in nonviolent *and* violent dissent, while also going beyond self-determination or ethnonationalist movements (Wilkenfeld et al., 2011; Cunningham et al., 2020), or armed rebel groups (Pettersson & Öberg, 2020; Harbom et al., 2008; Braithwaite & Cunningham, 2020; Stewart, 2018; Cunningham, 2013; Svensson & Nilsson, 2018; Cunningham et al., 2009). Events datasets often identify participating actors, but lack information on their features (Chenoweth et al., 2018, 2019; Salehyan et al., 2012; Clark & Regan, 2021; Raleigh et al., 2010; Chenoweth et al., 2019). The Revolutionary and Militant Organizations Dataset does provide information about resistance organizations but seems to oversample on violent organizations (75% of REVMOD organization-years are rebel or terrorist groups) and does not account for relationships between organizations (Acosta, 2019). ARC is unique in capturing inter-organizational ties that help us understand network structures in resistance episodes.

Creating ARC

To construct the ARC dataset, we first identified organizations that participated in events of maximalist collective dissent and then recorded information on the features of those

[1] A series of borderline demands and their treatment can be found at the ARC project website.

organizations. To maximize transparency and replicability, coding decisions at each step were recorded in RMarkdown files.[2]

Identifying participants

Participating organizations were identified by drawing on five events datasets: the UCDP Georeferenced Event Dataset (Sundberg & Melander, 2013), the Social Conflict Analysis Dataset (Salehyan et al., 2012), the Mass Mobilization Dataset (Clark & Regan, 2021), the Armed Conflict Location Event Dataset (Raleigh et al., 2010), and the NAVCO 3.0 data covering African countries (Chenoweth et al., 2018). Together, these datasets provide a comprehensive catalogue of nonviolent and violent collective dissent across Africa. We began by creating a list of *candidate* maximalist events by sub-setting on variables related to dissident demands and a customized text-matching string.

We then determined whether event participants made maximalist demands and whether one or more named organizations participated by conducting newswire searches in FACTIVA and LexisNexis using a targeted search string. Event IDs from the events datasets are stored with the organization-year observations in ARC, allowing users to integrate variables from events data with ARC.

We added the constituent organizations of "fronts" according to a "three year" rule. Fronts are distinct, umbrella organizations coordinating the actions of member organizations. Some projects like the UCDP treat fronts as unitary actors, but this obscures variation in the preferences and features of member organizations. However, always treating fronts as decentralized organizational networks can be impractical - and empirically inaccurate. Fronts often become more unified over time (or they split apart) but systematically determining when a front ceases to consist of semi-autonomous groups and becomes a single organization is extremely difficult. We adopted an arbitrary but empirically informed rule to resolve this issue, whereby member organizations of a front were added as participants when those organizations had been members of the front for three or fewer years. Member

[2]Markdown files available on request.

organizations were identified in newswire databases, primary and secondary sources, and through an iterative process when information on their features was collected by coders. A more detailed description of the rules for coding fronts can be found in the codebook.

This three year rule means that some organizations may be included that were relatively new members of fronts but did not participate in protests, or played only a peripheral role. However, we argue that this risk is outweighed by the inclusion of organizations that often participate in protests but are overlooked by news media, such as local human rights organizations, women's organizations and youth groups. Since front participants are identified through newswires *and* primary and secondary sources, our inclusion criteria is less subject to media biases and provides a new, more comprehensive picture of opposition networks.

Coding organization features

This process produced a list of organizations linked to events of dissent. Organization-years of maximalist dissent were then generated from the events data and a team of coders recorded information on the features of participating organizations. Some variables are constant across organization-years (e.g. "birth date"), while others are dynamic. Organization-years were only coded when organizations were identified as participating in collective dissent with maximalist demands in a given year. Organizations often continue to exist when they are not participating in dissent; however, their non-participation means these observations are omitted from ARC. Constructing a full panel for organizations between 1990-2015 is not possible for this reason and because we do not record if and when organizations cease to exist (versus entering into abeyance). Table I summarizes several organization-feature variables in ARC.[3]

ARC includes information on two types of ties between organizations: fronts and alliances. Front ties connect a constituent organization to a higher-level organization (a front) when the constituent organization is formally a member of the front, or its leaders partici-

[3]The full codesheet can be found in the supplementary materials.

Table I. Organization-level variables

Variable	Description	Format
Type	Categorization of organization type	Categorical
Birthdate	Date organization was founded	Date: dd-mm-yyyy
Origins	How organization formed	Categorical: (Splinter, Merger, Other)
Goals	Primary organization goals	Open text
Size	Membership size in year	Numeric
Size Estimate	Approximate size	Ordinal
Leadership	Leader name/gender	Open text
Leadership Tenure	Date leader assumed position	Date: dd-mm-yyyy
Leadership Ties	Did leader serve at a high level in previous governments?	Categorical: (Yes/No)
Social Base	Main social group(s) in organization	Open text
Social Media	Extent of social media use	Categorical: (None, Some, Significant)
State Rel.	Relationship with state at t-1	Categorical
Formal Ties	Ties with other active organizations	String: Organization IDs
Structure I	Clear leadership/decision-making structure?	Categorical: (Yes/No)
Structure II	Characterised as 'decentralised'?	Categorical: (Yes/No)

pate in the front's leadership.[4] Organizations identified by the aforementioned "three year" rule have front ties to the main front.

Alliance ties connect two or more organizations that declared they were coordinating resistance activities, or sources indicated that organizations coordinated efforts, but they did not form a standalone organization (front) to manage coordination. Fronts and their constituent organizations can have alliance ties with non-front organizations. For example, in Malawi in 1993, the Public Affairs Committee (PAC, a front of CSOs and religious groups) allied with the Alliance for Democracy (a political party), which was not part of PAC. Users can assemble alliance-pairs with these front and alliance variables to explore factors driving inter-organizational ties.

Figure 1 illustrates these ties. The organization at the bottom-center has alliance ties to two other organizations and is a member of a front. That front is also a member of another front.

Our method for identifying organizations may create bias. Participation is coded when newswires identify named organizations engaged in maximalist dissent. Journalists may view some organizations – especially political parties and trade unions – as more deserving of a proper noun. Parties are skilled at attracting media attention and might be over-represented in reporting. Urban organizations may also be over-represented because events in cities receive more media coverage than events in rural locations (Kalyvas, 2004; Eck, 2012; Day et al., 2015).[5] Media biases could affect inferences drawn from ARC, so robustness tests such as those from Weidmann (2016) are recommended.

Maximalist demand-making is strategic and may occur after prior campaign-building, after high levels of past participation in non-maximalist protest, or when repression offers 'no other way out' (Goodwin, 2001) – factors that independently generate regime concessions or democratization (Brancati, 2016; Klein & Regan, 2018). Researchers should control for omitted variables capturing these selection processes wherever possible and inferences from

[4]In some cases, fronts themselves become constituent organizations in higher-level fronts. In this case, we only include ties from constituent organizations to the closest-level front in the hierarchy.

[5]Urban organizations may also be more frequent participants because organizations and collective action are more common in cities (Weidmann & Rød, 2018; Nicholls, 2008; Miller & Nicholls, 2013).

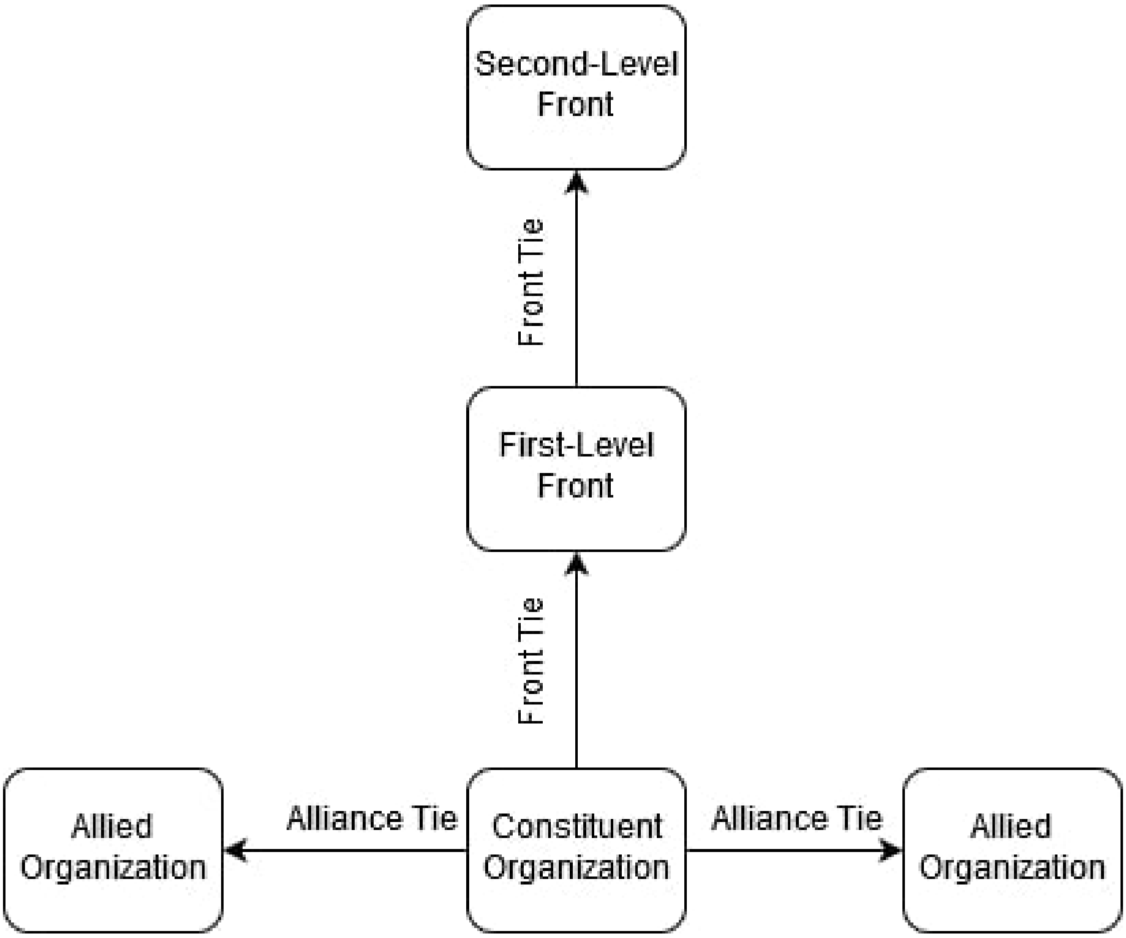

Figure 1. ARC ties example

ARC should be informed by the limitations of selecting on maximalist demands.

ARC is limited to African countries from 1990-2015 for practical reasons driven by overlap in available events datasets. However, by building on existing datasets, we augment those resources while also maximizing compatibility. African countries' histories of contention, civil society, and statehood are unique and context-specific and we direct readers to studies that provide useful background (Boone, 2003; Branch & Mampilly, 2015; Bratton & van de Walle, 1997; Herbst, 2014; Mueller, 2018).

While inferences drawn from ARC only apply with confidence to the African continent, our method of building upon existing event-based resources is transportable to other regions, time periods, and non-maximalist dissent – extensions we plan to offer in the future.

Table II shows continuous measurements of ideological diversity and opposition unity generated from ARC and compares them to similar (but categorical) measures in the NAVCO 2.1 dataset (Chenoweth & Shay, 2019) from Egypt between 2003-2015. ARC also encompasses years of democratic transition, identifies more organizations, and enables new measurements of features such as organization age. Figure 2 shows a network map for Egypt in 2011, generated using front and alliance variables in ARC.

Table II. Comparison of ARC and NAVCO 2.1: Egypt 2003-2015

	NAVCO 2.1			ARC			
Year	Religious diversity	Unity[a]	New orgs	No. orgs	Unity[b]	Diversity[g]	Mean age[c]
2003	Yes	Seemingly united	3	10	0.750	0.72	17
2004	Yes	Moderate disunity	11	7	0.710	0.73	17
2005	Yes	Moderate disunity	6	9	0.765	0.77	23
2006	NA	NA	NA	9	0.793	0.77	24
2007	No	Seemingly united	1	9	0.793	0.77	25
2008	No	Moderate disunity	1	2	0	0.5	40
2009	No	Moderate disunity	1	3	1	0.67	29
2010	No	Moderate disunity	3	13	0.701	0.71	21
2011	Yes	Seemingly united	3	41	0.850	0.79	9
2012	NA	NA	NA	64	0.843	0.82	11
2013[d]	No[f]	Seemingly united[e]	6	74	0.874	0.82	9
2014	NA	NA	NA	30	0.901	0.74	9
2015	NA	NA	NA	15	0.846	0.61	12

[a] Measured with the 'camp_conf_intensity' variable. [b] Measured as the network centralization score, which captures the extent to which a network coheres around (or is united by) one focal point (often a single front in our case). [c] In years for valid observations. [d] NAVCO 2.1 features three campaigns in 2013. [e] All three campaigns were 'Seemingly United.' [f] No religious diversity was recorded across all three campaigns. [g] Legend is visualised in the network map

below. Organizations that don’t fit into these categories are grey. Embedded numbers are fractionalization index scores

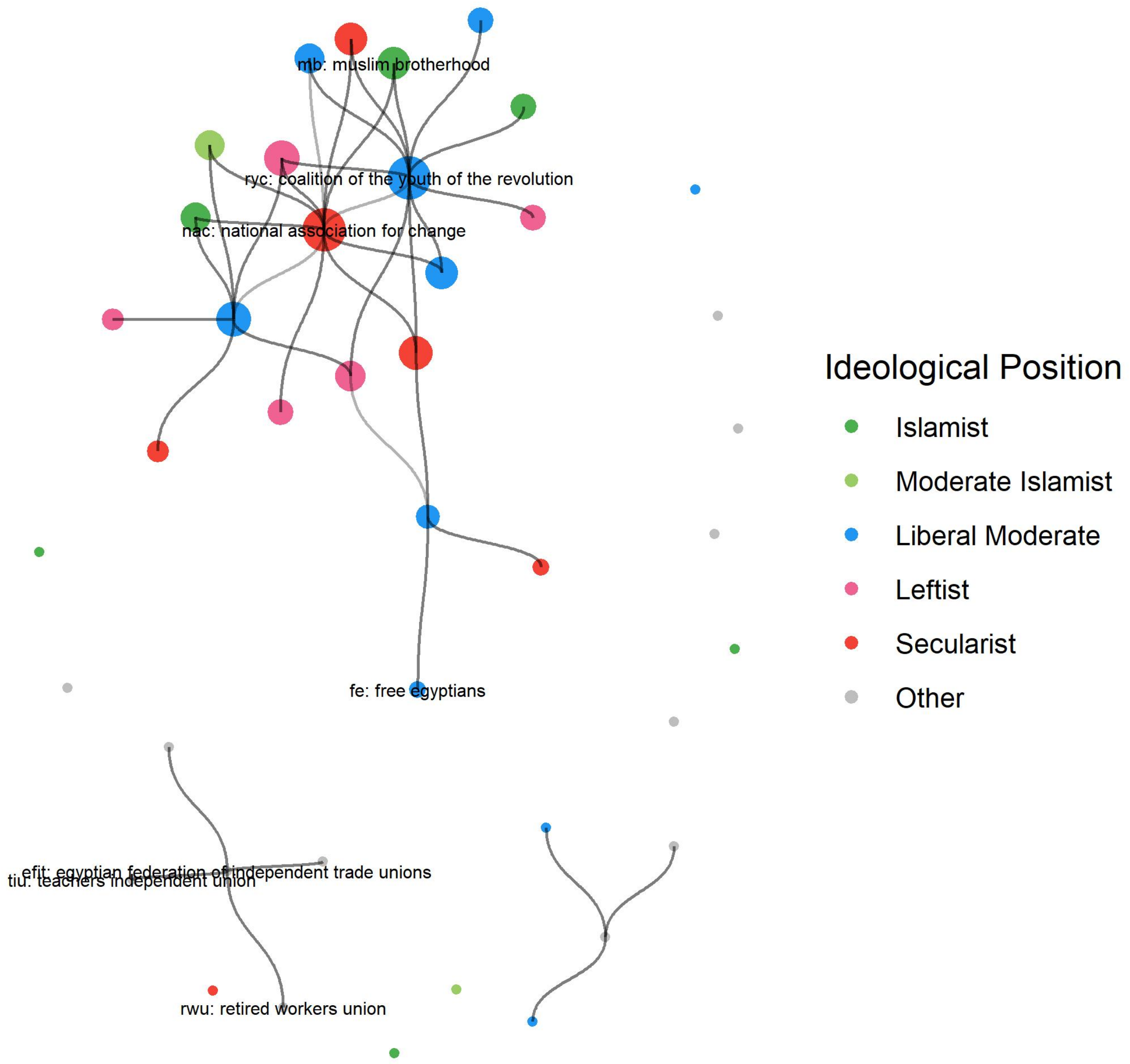

Figure 2. Egypt 2011[g]

[g]Node sizes are proportional to degree centrality. Ideological positions were generated with text-matching on the organization-goals variable (see Appendix). Named organizations have a centrality score over > 0.6 or an estimated membership size of more than 100,000

Descriptive statistics

Political parties and rebel groups[6] are the most common types of organizations in ARC. Figure 3 shows the number of organizations in maximalist dissent by year and country. Stretches of little dissent are sometimes followed by bursts (Burkina Faso), while the number of organizations in dissent escalates over time in other cases (Sudan). Some countries exhibit consistently high numbers of organizations in dissent (Ethiopia) while others are stable and low (Namibia).

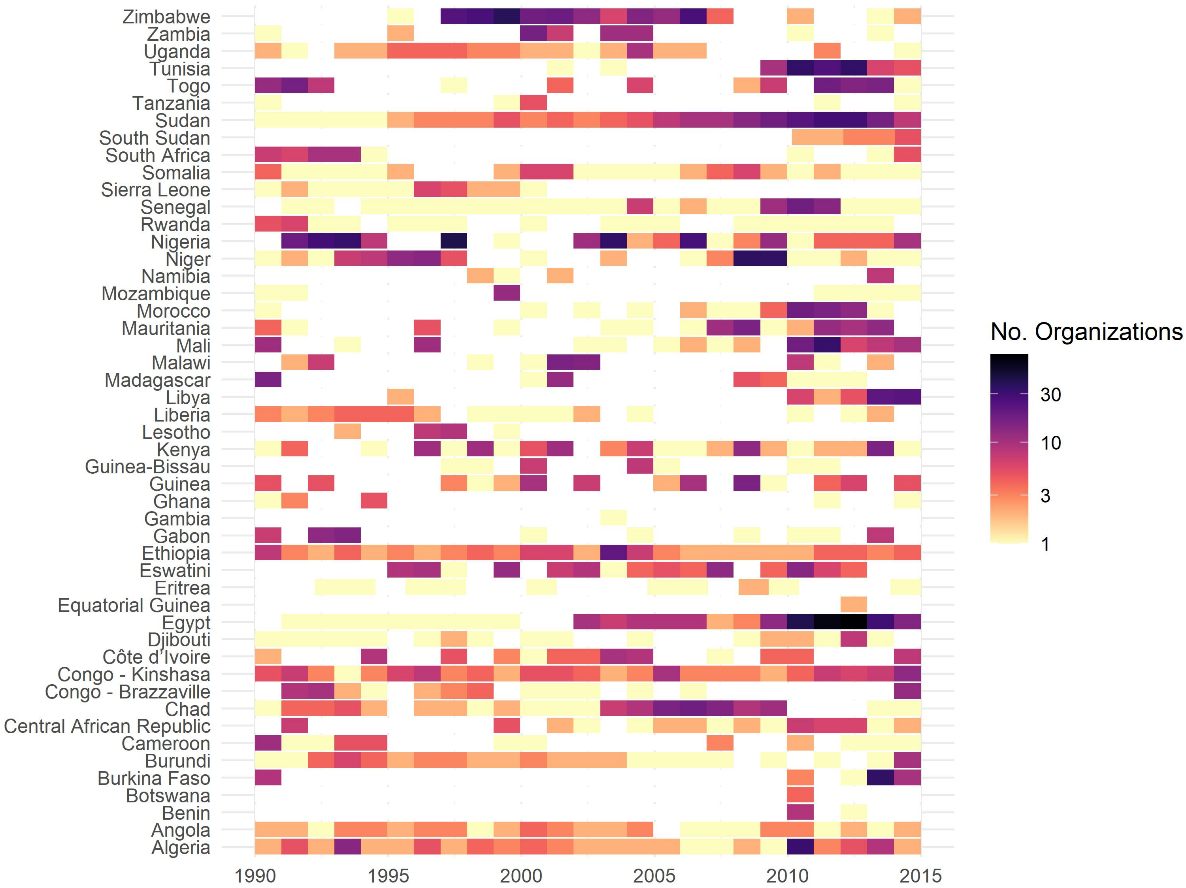

Figure 3. ARC organizations over time and space

Table III shows how ARC variables vary across organization types.

[6]We use the term rebel group to characterize armed groups explicitly organized to challenge the state using violence; this does not require involvement in conflicts with 25+ battle deaths as with UCDP coding rules, but rather follows the logic of Lewis (2020).

Table III. Features of Organization-Years in Resistance by Type

Type	N	N Unique Orgs.	Splinter	Size Estimate	Age	Included in Regime	Legal	\# Ties	Female Leader	Dece
Pol. Party	1143	532	0.27	3	6.51	0.08	0.7	1.2	0.02	
Trade Union	214	96	0.16	4	24.06	0.06	0.83	1.87	0.05	
Religious	101	42	0	3	32.85	0.02	0.95	1.38	0	
Student/Youth	69	27	0.09	3	17.62	0.03	0.55	1.52	0	
Front	262	157	0.01	3	2.01	0.03	0.33	6.67	0.06	
Other CSO	558	297	0.08	2	10.13	0.01	0.72	1.51	0.19	
Rebel	1004	273	0.4	3	7.63	0.02	0.03	1.32	0	
Other	44	26	0.2	3	9.65	0.02	0.5	1	0.13	
Missingness (\%)			0.12	0.17	0.08	0.03	0.03	NA	0.12	

All summary statistics are means except for the Size Estimate which is a median. *Included* measures whether the organization was formally or infor

Rebel groups and parties commonly split from other organizations. Rebel groups dissent for longer (3.6 years on average) and more continuously (they have the lowest variance around the mean participation year) than other organizations. Participation by other types of organizations in ARC is "bursty," perhaps concentrated around elections or other focal points. Trade unions tend to be large, old, and more connected to the state and other opposition organizations than most other organizations. As one would expect, fronts are the most highly connected, with ties to 5.67 other organizations on average. Only CSOs have moderate levels of female leadership. Decentralization is most common in fronts, religious groups, and trade unions.

Correlates of organizational participation

Different types of organizations should have distinct correlates of participation in resistance given their varied constituencies and goals.[7] We explore associations between socioeconomic factors and the number of organizations of different types active in maximalist dissent using Negative Binomial models for over-dispersed count data. Specifically, we examine inequality, economic modernization, industrialization, economic growth, natural resource wealth, democratic institutions, the number of other participating dissident organizations of various types and a lagged dependent variable. Past research highlights these possible explanations for participation in maximalist dissent (Acemoglu & Robinson, 2005; Ansell & Samuels, 2014; Ross, 2001; Bueno de Mesquita & Smith, 2010; Haggard & Kaufman, 2016; Maves & Braithwaite, 2013; Aksoy et al., 2012).

Income inequality (and its square) is captured using Gini coefficients.[8] Economic development is measured with GDP per capita in constant 2000 USD, along with the GDP growth rate to proxy economic downturns. Value-added manufacturing as a % of GDP represents the strength of the industrial sector (Haggard & Kaufman, 2016; Butcher & Svensson, 2016) and oil revenues as a % of GDP proxy for natural resource dependency. We measure

[7]Models were run in R 4.0.2

[8]Data come from the World Bank unless indicated otherwise.

prior political institutions with the V-DEM Polyarchy score (**?**), as well as its square (Hegre & Sambanis, 2006). Repression is measured with the Physical Violence Index, also from VDEM. These variables are lagged one year. The number of organizations of other types engaged in maximalist dissent in year t is included to explore patterns of co-participation across organization-types.

Table IV presents our findings. Visualizations can be found in the Appendix. The results for economic development are striking. More rebel groups mobilize in poorer countries, while more trade unions, student organizations, and other CSOs dissent in more developed countries. Broad, labor-based civil society coalitions may be an important link in the chain from modernization to democracy (Chenoweth & Stephan, 2011; Celestino & Gleditsch, 2013; Bayer et al., 2016; Dahlum et al., 2019; Boix, 2003). Movements underpinned by thinner, technology-driven networks may be more brittle (Weidmann & Rød, 2018). Oil dependency is associated with fewer trade unions, student groups, "other" organizations, and religious organizations engaging in maximalist dissent, but more active rebel groups. These models are a first, descriptive look at patterns of participation that say little about the deeper mechanisms, however. For example, structural factors may alter the underlying organizational ecology, drive participation in maximalist dissent directly, or activate other processes, such as splintering.

Structural variables appear to be poor predictors of the number of fronts in dissent. Coalition formation may occur after shorter term shocks related to food prices (Abbs, 2020) or severe repression events (Chang, 2008). This is worth investigating in future work. Models addressing censorship and international media coverage (in the appendix) do not indicate strong media biases across most organization types.

	Political Parties	Trade Unions	Rel. Orgs	Student/Youth	Fronts	Rebel Groups	Other CSOs	Others
Oil (% GDP)	-0.01	-0.09^{**}	-0.27^{**}	-0.08^{*}	-0.01	0.03^{***}	-0.02	-0.61^{**}
	(0.01)	(0.03)	(0.09)	(0.03)	(0.01)	(0.01)	(0.01)	(0.23)
Manufacturing (% GDP)	0.02	0.00	0.09	0.13^{***}	-0.01	0.02^{*}	0.01	0.07
	(0.01)	(0.02)	(0.05)	(0.03)	(0.02)	(0.01)	(0.02)	(0.07)
Polyarchy	7.19^{**}	-2.23	17.24	1.76	2.79	-1.65	6.12	12.46
	(2.52)	(5.19)	(9.88)	(6.40)	(2.86)	(1.68)	(3.84)	(11.00)
Polyarchy ^{2}	-10.26^{***}	0.42	-29.11^{*}	0.31	-3.96	1.16	-5.76	-16.34
	(2.95)	(5.79)	(12.07)	(7.68)	(3.30)	(2.05)	(4.20)	(12.70)
Income Inequality ^{2}	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Income Inequality	-0.03	0.10	0.11	0.20	0.09	-0.04	0.24	-0.43
	(0.09)	(0.18)	(0.28)	(0.22)	(0.10)	(0.06)	(0.13)	(0.27)
Log GDP per Capita	0.03	0.79^{**}	-0.33	0.85^{**}	0.12	-0.51^{***}	0.58^{**}	0.94^{*}
	(0.13)	(0.26)	(0.41)	(0.33)	(0.13)	(0.09)	(0.18)	(0.47)
GDP Growth	0.81	-4.24^{*}	-1.07	-0.42	-0.29	0.09	-1.28	4.66
	(0.87)	(1.87)	(3.21)	(1.97)	(0.94)	(0.53)	(1.39)	(4.06)
Physical Integrity Rights	0.02	0.33	0.30	-4.96^{**}	-0.96	-0.40	-1.40^{*}	-3.90^{*}
	(0.46)	(0.92)	(1.70)	(1.55)	(0.53)	(0.33)	(0.71)	(1.76)
Year	0.01	0.04	0.14^{**}	0.03	-0.01	0.00	0.08^{***}	0.07
	(0.01)	(0.02)	(0.04)	(0.03)	(0.01)	(0.01)	(0.02)	(0.04)
Population (Log)	0.08	-0.28^{*}	0.47	0.13	0.04	0.26^{***}	0.39^{***}	0.78^{*}
	(0.07)	(0.14)	(0.30)	(0.20)	(0.08)	(0.05)	(0.10)	(0.34)
No. Political Parties		0.11^{*}	0.31^{***}	-0.01	0.19^{***}	-0.01	0.10^{**}	0.02
		(0.05)	(0.08)	(0.04)	(0.02)	(0.02)	(0.04)	(0.06)
No. Trade Unions	0.06		-0.01	0.28^{**}	0.29^{***}	0.00	0.39^{***}	0.25
	(0.09)		(0.23)	(0.10)	(0.05)	(0.08)	(0.10)	(0.20)
No. Rel. Orgs	0.15	0.23^{*}		0.24^{*}	0.15^{*}	-0.18	0.41^{***}	0.21
	(0.09)	(0.12)		(0.10)	(0.07)	(0.14)	(0.09)	(0.14)
No. Student/Youth Orgs	-0.07	0.44	0.02		-0.24	-0.28	0.61^{**}	-0.20
	(0.23)	(0.28)	(0.55)		(0.17)	(0.17)	(0.23)	(0.37)
No. Fronts	1.71^{***}	0.88^{***}	0.38	0.16		0.11	0.93^{***}	0.18
	(0.12)	(0.18)	(0.36)	(0.18)		(0.09)	(0.17)	(0.41)
No. Rebel Groups	-0.17^{***}	-0.19	-0.18	0.25^{***}	0.25^{***}		-0.27^{***}	-0.01
	(0.04)	(0.11)	(0.23)	(0.05)	(0.03)		(0.07)	(0.24)
No. CSOs	0.01	0.16^{***}	0.51^{***}	0.10^{**}	0.09^{***}	0.00		0.15^{**}
	(0.03)	(0.04)	(0.08)	(0.03)	(0.02)	(0.03)		(0.06)
No. Others	-0.40^{*}	-0.52^{*}	-2.53^{***}	0.01	-0.55^{***}	0.12	-0.53^{*}	
	(0.20)	(0.25)	(0.52)	(0.20)	(0.13)	(0.15)	(0.21)	
No. Political Parties (t-1)	0.11^{***}							
	(0.02)							
No. Trade Unions (t-1)		0.33^{***}						
		(0.10)						
No. Rel. Orgs (t-1)			0.47^{**}					
			(0.17)					
No. Student/Youth Orgs (t-1)				0.38^{*}				
				(0.18)				
No. Fronts (t-1)					-0.08			
					(0.09)			
No. Rebel Groups (t-1)						0.29^{***}		
						(0.02)		
No. CSOs (t-1)							0.07^{*}	
							(0.03)	
No. Others (t-1)								0.37^{*}
								(0.19)
AIC	1918.39	606.68	334.35	270.20	798.84	1743.83	1018.85	177.61
BIC	2020.66	708.95	436.62	372.47	901.11	1846.10	1121.12	279.88
Log Likelihood	-938.19	-282.34	-146.17	-114.10	-378.42	-850.91	-488.42	-67.81
Deviance	592.27	202.48	85.70	128.22	359.43	699.10	332.07	84.89
Num. obs.	963	963	963	963	963	963	963	963

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table IV. Correlates of Organizational Participation

Table IV also reveals patterns of organizational cross-participation. Parties mobilize with fronts, but alongside fewer rebel groups. Trade unions and CSOs dissent alongside one another and with more parties, religious organizations, and fronts. Religious organizations have narrower co-participation profiles, mobilizing alongside other CSOs. Student groups dissent alongside rebel groups, in addition to trade unions, religious organizations, and other CSOs. Rebel groups tend to act without high numbers of other types of organizations. Finally, fronts assemble many group types including parties, rebels, trade unions, religious organizations, and other CSOs.

These findings highlight the usefulness of ARC for (re)examining mechanisms highlighted in theories of social change, as well as the ability to uncover novel, previously un(der)theorized relationships.

Conclusion

The ARC dataset advances our understanding of anti-government mobilization and has many potential applications. ARC provides details about organizations that engaged in violent and nonviolent dissent at various periods of their existence and could be used to identify correlates of tactical shifts. ARC should be useful to scholars of repression and dissent; connections to events datasets facilitate exploration of how organizational networks interact with repression to produce backlash and demobilization. ARC can also be collapsed into country-year format and merged with data on campaign outcomes (e.g. Chenoweth & Shay (2019), Kreutz (2010)), regime change, and democratization (Goemans et al., 2009; Djuve et al., 2020; **?**). Information on inter-organizational ties can be used to generate network maps that span conventional violent-nonviolent dichotomies and even link campaigns cross-nationally. We look forward to seeing how others engage ARC to expand our knowledge of the causes, dynamics, and consequences of maximalist dissent.

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References

Abbs, L. (2020). The hunger games: Food prices, ethnic cleavages and nonviolent unrest in Africa. *Journal of Peace Research*, *57*(2), 281–296.

Acemoglu, D. & Robinson, J. A. (2005). *Economic Origins of Dictatorship and Democracy.* New York: Cambridge University Press.

Acosta, B. (2019). Reconceptualizing resistance organizations and outcomes: Introducing the Revolutionary and Militant Organizations dataset (REVMOD). *Journal of Peace Research*, *56*(5), 724–734.

Aksoy, D., Carter, D. B., & Wright, J. (2012). Terrorism In Dictatorships. *The Journal of Politics*, *74*(3), 810–826.

Ansell, B. W. & Samuels, D. J. (2014). *Inequality and Democratization.* Cambridge, UK: Cambridge University Press.

Bayer, M., Bethke, F. S., & Lambach, D. (2016). The democratic dividend of nonviolent resistance. *Journal of Peace Research*, *53*(6), 758–771.

Belgioioso, M. (2018). Going underground: Resort to terrorism in mass mobilization dissident campaigns. *Journal of Peace Research*, *55*(5), 641–655.

Bethke, F. S. & Pinckney, J. (2019). Non-violent resistance and the quality of democracy. *Conflict Management and Peace Science*, 0738894219855918.

Boix, C. (2003). *Democracy and Redistribution*. New York: Cambridge University Press.

Boone, C. (2003). *Political Topographies of the African State: Territorial Authority and Institutional Choice*. Cambridge, UK: Cambridge University Press.

Braithwaite, J. M. & Cunningham, K. G. (2020). When Organizations Rebel: Introducing the Foundations of Rebel Group Emergence (FORGE) Dataset. *International Studies Quarterly*, *64*(1), 183–193.

Brancati, D. (2016). *Democracy Protests*. New York: Cambridge University Press.

Branch, A. & Mampilly, Z. (2015). *Africa Uprising: Popular Protest and Political Change*. London, UK: Zed Books.

Bratton, M. & van de Walle, N. (1997). *Democratic Experiments in Africa: Regime Transitions in Comparative Perspective*. Cambridge, UK: Cambridge University Press.

Bueno de Mesquita, B. & Smith, A. (2010). Leader Survival, Revolutions, and the Nature of Government Finance. *American Journal of Political Science*, *54*(4), 936–950.

Butcher, C. & Svensson, I. (2016). Manufacturing Dissent: Modernization and the Onset of Major Nonviolent Resistance Campaigns. *Journal of Conflict Resolution*, *60*(2), 311–339.

Celestino, M. R. & Gleditsch, K. S. (2013). Fresh carnations or all thorn, no rose? Nonviolent campaigns and transitions in autocracies. *Journal of Peace Research*, *50*(3), 385–400.

Chang, P. Y. (2008). Unintended Consequences of Repression: Alliance Formation in South Korea's Democracy Movement (1970–1979). *Social Forces*, *87*(2), 651–677.

Chenoweth, E., Hendrix, C. S., & Hunter, K. (2019). Introducing the Nonviolent Action in Violent Contexts (NVAVC) dataset. *Journal of Peace Research*, *56*(2), 295–305.

Chenoweth, E., Pinckney, J., & Lewis, O. (2018). Days of rage: Introducing the NAVCO 3.0 dataset. *Journal of Peace Research*, *55*(4), 524–534.

Chenoweth, E. & Shay, C. W. (2019). NAVCO 2.1 Dataset.

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

Clark, D. & Regan, P. (2021). Mass Mobilization Protest Data.

Collier, R. B. (1999). *Paths toward Democracy: The Working Class and Elites in Western Europe and South America*. New York: Cambridge University Press.

Cunningham, D. E., Gleditsch, K. S., González, B., Vidović, D., & White, P. B. (2017). Words and deeds: From incompatibilities to outcomes in anti-government disputes. *Journal of Peace Research*, *54*(4), 468–483.

Cunningham, D. E., Skrede Gleditsch, K., & Salehyan, I. (2009). It Takes Two: A Dyadic Analysis of Civil War Duration and Outcome. *Journal of Conflict Resolution*, *53*(4), 570–597.

Cunningham, K. G. (2013). Actor Fragmentation and Civil War Bargaining: How Internal Divisions Generate Civil Conflict. *American Journal of Political Science*, *57*(3), 659–672.

Cunningham, K. G., Dahl, M., & Frugé, A. (2020). Introducing the Strategies of Resistance Data Project. *Journal of Peace Research*, *57*(3), 482–491.

Daft, R. L. (1992). *Organization Theory and Design*. St Paul, MN: West Publishing.

Dahlum, S., Knutsen, C. H., & Wig, T. (2019). Who Revolts? Empirically Revisiting the Social Origins of Democracy. *The Journal of Politics*, *81*(4), 1494–1499.

Day, J., Pinckney, J., & Chenoweth, E. (2015). Collecting data on nonviolent action: Lessons learned and ways forward. *Journal of Peace Research*, *52*(1), 129–133.

Djuve, V. L., Knutsen, C. H., & Wig, T. (2020). Patterns of Regime Breakdown Since the French Revolution. *Comparative Political Studies*, *53*(6), 923–958.

Eck, K. (2012). In data we trust? A comparison of UCDP GED and ACLED conflict events datasets. *Cooperation and Conflict*, *47*(1), 124–141.

Gleditsch, K. S., Metternich, N. W., & Ruggeri, A. (2014). Data and progress in peace and conflict research. *Journal of Peace Research*, *51*(2), 301–314.

Goemans, H. E., Gleditsch, K. S., & Chiozza, G. (2009). Introducing Archigos: A Dataset of Political Leaders. *Journal of Peace Research*, *46*(2), 269–283.

Goodwin, J. (2001). *No Other Way Out: States and Revolutionary Movements, 1945-1991*. Cambridge, UK: Cambridge University Press.

Haggard, S. & Kaufman, R. R. (2016). *Dictators and Democrats: Masses, Elites, and Regime Change*. Princeton, NJ: Princeton University Press.

Harbom, L., Melander, E., & Wallensteen, P. (2008). Dyadic Dimensions of Armed Conflict, 1946—2007. *Journal of Peace Research*, *45*(5), 697–710.

Hegre, H. & Sambanis, N. (2006). Sensitivity Analysis of Empirical Results on Civil War Onset. *Journal of Conflict Resolution*, *50*(4), 508–535.

Herbst, J. (2014). *States and Power in Africa: Comparative Lessons in Authority and Control*, volume 149. Princeton, NJ: Princeton University Press.

Huang, R. (2016). *The Wartime Origins of Democratization: Civil War, Rebel Governance, and Political Regimes*. New York: Cambridge University Press.

Kalyvas, S. N. (2004). The Urban Bias in Research on Civil Wars. *Security Studies*, *13*(3), 160–190.

Klein, G. R. & Regan, P. M. (2018). Dynamics of Political Protests. *International Organization*, *72*(2), 485–521.

Kreutz, J. (2010). How and when armed conflicts end: Introducing the UCDP Conflict Termination dataset. *Journal of Peace Research*, *47*(2), 243–250.

Lewis, J. I. (2020). *How Insurgency Begins: Rebel Group Formation in Uganda and Beyond*. Cambridge, UK: Cambridge University Press.

Maves, J. & Braithwaite, A. (2013). Autocratic Institutions and Civil Conflict Contagion. *The Journal of Politics*, *75*(2), 478–490.

McAdam, D. (2010). *Political Process and the Development of Black Insurgency, 1930-1970*. University of Chicago Press.

Metternich, N. W., Dorff, C., Gallop, M., Weschle, S., & Ward, M. D. (2013). Antigovernment Networks in Civil Conflicts: How Network Structures Affect Conflictual Behavior. *American Journal of Political Science*, *57*(4), 892–911.

Miller, B. & Nicholls, W. (2013). Social Movements in Urban Society: The City as A Space of Politicization. *Urban Geography*, *34*(4), 452–473.

Mueller, L. (2018). *Political Protest in Contemporary Africa*. Cambridge, UK: Cambridge University Press.

Nepstad, S. E. (2011). *Nonviolent Revolutions: Civil Resistance in the Late 20th Century*. Oxford, UK: Oxford University Press.

Nicholls, W. J. (2008). The Urban Question Revisited: The Importance of Cities for Social Movements. *International Journal of Urban and Regional Research*, *32*(4), 841–859.

North, D. C. (1990). *Institutions, Institutional Change and Economic Performance*. New York: Cambridge University Press.

Osa, M. (2003). *Solidarity And Contention: Networks Of Polish Opposition*. Minneapolis, MN: University Of Minnesota Press.

Pearlman, W. (2011). *Violence, Nonviolence, and the Palestinian National Movement*. Cambridge, UK: Cambridge University Press.

Pettersson, T. & Öberg, M. (2020). Organized violence, 1989–2019. *Journal of Peace Research*, *57*(4), 597–613.

Pinckney, J. C. (2020). *From Dissent to Democracy: The Promise and Perils of Civil Resistance Transitions*. New York: Oxford University Press.

Raleigh, C., Linke, A., Hegre, H., & Karlsen, J. (2010). Introducing ACLED: An Armed Conflict Location and Event Dataset: Special Data Feature. *Journal of Peace Research*, *47*(5), 651–660.

Ross, M. L. (2001). Does Oil Hinder Democracy? *World Politics*, *53*(3), 325–361.

Salehyan, I., Hendrix, C. S., Hamner, J., Case, C., Linebarger, C., Stull, E., & Williams, J. (2012). Social Conflict in Africa: A New Database. *International Interactions*, *38*(4), 503–511.

Schaftenaar, S. (2017). How (wo)men rebel: Exploring the effect of gender equality on nonviolent and armed conflict onset. *Journal of Peace Research*, *54*(6), 762–776.

Schock, K. (2005). *Unarmed Insurrections: People Power Movements in Nondemocracies*. Minneapolis, MN: University of Minnesota Press.

Siegel, D. A. (2009). Social Networks and Collective Action. *American Journal of Political Science*, *53*(1), 122–138.

Stewart, M. A. (2018). Civil War as State-Making: Strategic Governance in Civil War. *International Organization*, *72*(1), 205–226.

Sundberg, R. & Melander, E. (2013). Introducing the UCDP Georeferenced Event Dataset. *Journal of Peace Research*, *50*(4), 523–532.

Sutton, J., Butcher, C. R., & Svensson, I. (2014). Explaining Political Jiu-Jitsu: Institution-Building and the Outcomes of Regime Violence against Unarmed Protests. *Journal of Peace Research*, *51*(5), 559–573.

Svensson, I. & Lindgren, M. (2011). Community and consent: Unarmed insurrections in non-democracies. *European Journal of International Relations*, *17*(1), 97–120.

Svensson, I. & Nilsson, D. (2018). Disputes over the Divine: Introducing the Religion and Armed Conflict (RELAC) Data, 1975 to 2015. *Journal of Conflict Resolution*, *62*(5), 1127–1148.

Tarrow, S. G. (2011). *Power in Movement: Social Movements and Contentious Politics.* Cambridge, UK: Cambridge University Press.

Thurber, C. (2019). Social Ties and the Strategy of Civil Resistance. *International Studies Quarterly*, *63*(4), 974–986.

Tilly, C. (1978). *From Mobilization to Revolution.* Addison-Wesley, MA: Reading.

Weidmann, N. B. (2016). A Closer Look at Reporting Bias in Conflict Event Data. *American Journal of Political Science*, *60*(1), 206–218.

Weidmann, N. B. & Rød, E. G. (2018). *The Internet and Political Protest in Autocracies.* New York: Oxford University Press.

Wilkenfeld, J., Asal, V., & Pate, A. (2011). Minorities at Risk Organizational Behavior (MAROB) Middle East, 1980-2004.

Wood, E. J. (2000). *Forging Democracy from below: Insurgent Transitions in South Africa and El Salvador.* New York: Cambridge University Press.

Introducing the Anatomy of Resistance Campaigns (ARC) dataset: Appendix

March 12, 2021

1 Models with Indicators of Government Censorship and International Media coverage

The models below include two measures capturing aspects of the media environment at the country year level. The first is "Government Censorship Effort" from the VDEM dataset (Coppedge et al., 2019). Low values indicate that the media is highly censored while higher values indicate higher levels of media freedom. The second is a count of the number of Agence France Press and Associated Press newswire hits that are obtained with the country name in the headline or lead paragraph over a country-year. Chad is not included in these models because we were unable to create a search string that reliably separated the country 'Chad' from the personal name Chad. The results for other variables in the model are very similar to those in the main text, and we have excluded them from the table to focus on the media-related variables.

	Political Parties	Trade Unions	Rel. Orgs	Student/Youth	Fronts	Rebel Groups	Other CSOs	Others
								(0.19)
Count of FACTIVA newswire hits	0.00	-0.00^{**}	0.00	-0.00	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Media Freedom from Censorship	-0.09	0.55	-0.50	-0.01	-0.02	0.44^{***}	0.08	-0.94
	(0.14)	(0.29)	(0.44)	(0.43)	(0.16)	(0.09)	(0.21)	(0.58)
AIC	1790.60	576.89	333.12	261.24	709.52	1413.08	973.53	166.32
BIC	1901.20	687.50	443.73	371.85	820.13	1523.69	1084.13	276.93
Log Likelihood	-872.30	-265.45	-143.56	-107.62	-331.76	-683.54	-463.76	-60.16
Deviance	563.27	190.93	86.41	123.25	300.15	593.42	316.11	71.55
Num. obs.	906	906	906	906	906	906	906	906

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 1: Correlates of Organizational Participation, Media Variables

2 Coding the Religious Diversity Measure in the Main text

On pages 12 and 13 we show indicators of religious diversity over the years 2003-2015 in Egypt. These variables were generated from the ARC data with text-matching in R (version 4.0.2) on the organization goals variable according to the rules in the table below. The organization goals variable matches the text-matching pattern if any one of the listed strings matches with the words in the organization goals variable. For example, if any of the text in the organization goals variable matched the strings *secula* OR *antiislam* then this would return a positive match for the *Secularist* variable. White space and punctuation was removed from the words before the text-matching was used.

Table 2: Organization Size Estimate

Category	Coding Rule
Islamist	islam OR sharia OR jihad OR emirat OR salaf OR caliphat OR sunni OR muslim
Moderate Islamist	Islamist = TRUE and Liberal Moderate = TRUE
Moderate Liberal	liberal OR moderat OR centr OR center OR democra OR civilandlegalrights OR multiparty OR egalitarian OR electionintegrity OR civilsociety OR equality OR humanrights OR freedom OR plural OR freeelections OR fairelections OR libert OR suffrage OR freepress OR progressive OR humanist OR inclus AND Islamist = FALSE AND Moderate Islamist = FALSE AND Secular = FALSE AND Leftist=FALSE AND Christian = FALSE
Leftist	left OR anticapitalist OR socialis OR marx OR lenin OR trotsky OR communis OR class OR redistribution OR anticapital OR nationalization OR nationalizedeconomy
Secularist	secula OR antiislam AND Leftist = FALSE
Christian	christ OR evangel OR catholic OR gospel OR prosel OR biblic OR coptic
Other	Does not match any of the above patterns

3 Visualisations of the main results

Below are two figures that visualise the main results from Table 4 in the main text. Figure 1 plots the predicted number of organizations of a given type for different values of the structural variables in the model. These estimates were generated using the `ggeffects` package in `R`. Figure 2 visualises organization types that tend to participate together with a network graph, based on the results in Table 4 regarding how the participation of organization types is associated with the participation on other organization type. Organization-types have ties between them where we found a positive and statistically significant average marginal effect between the participation of organization type i and organization type j. The width of the ties is proportional to the size of the average marginal effects. Figure 2 shows that rebel groups and "other" organizations tend to act alone, while fronts are most strongly associated with political party, trade union and "Other CSO" participation. Trade Unions tend to participate with CSOs, which in turn have relatively strong associations with the participation of religious groups and student/youth organizations.

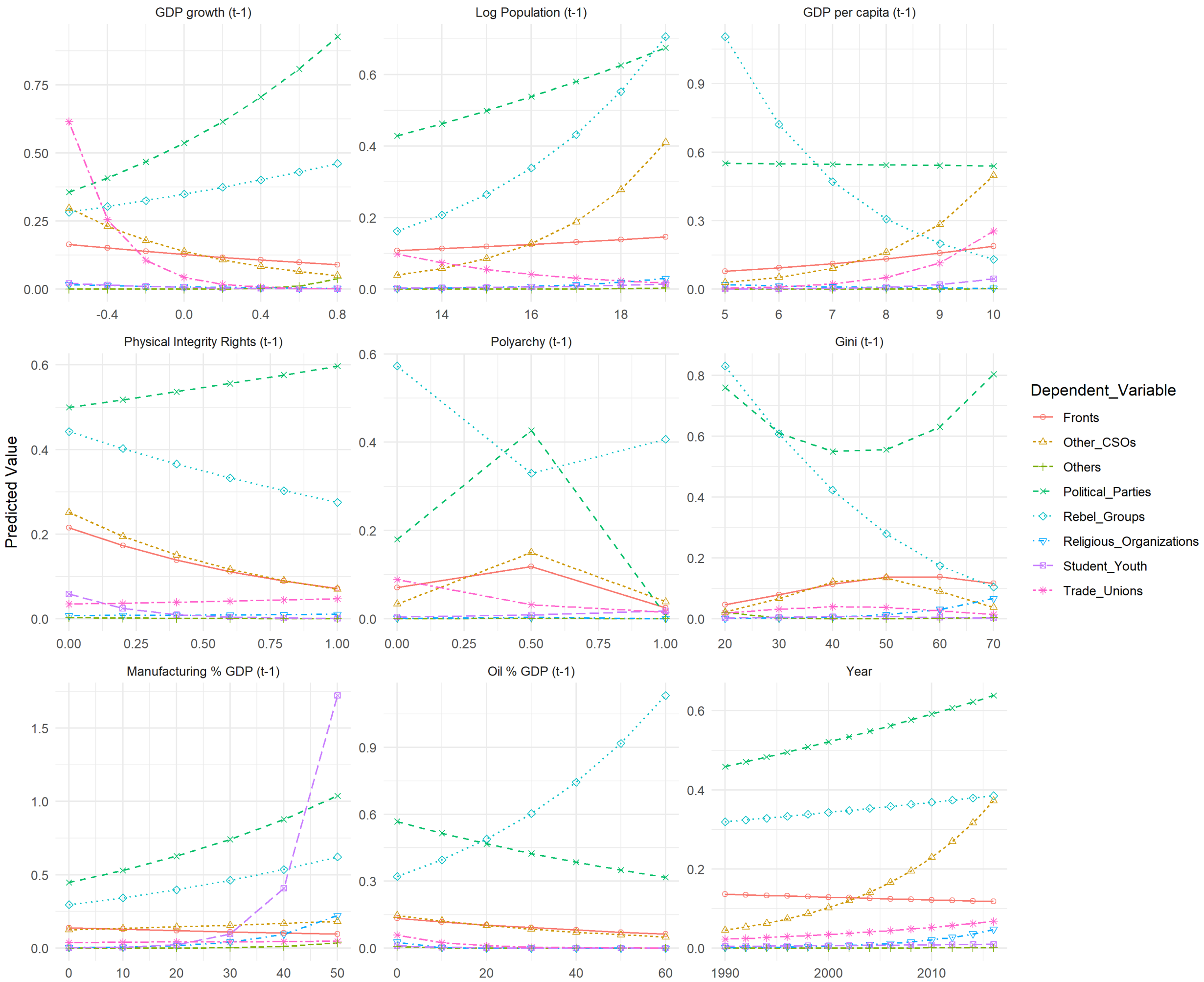

Figure 1: Visualizations: Main Results in the Text, Structural Variables

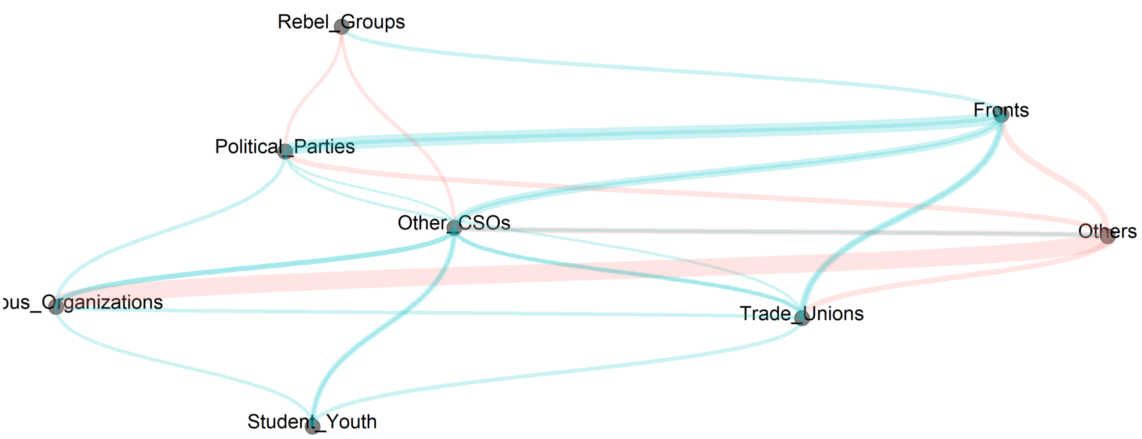

Figure 2: Visualizations: Clustering of Organization Types in Country-Years

References

Coppedge, M., Gerring, J., Knutsen, C. H., Lindberg, S. I., Skaaning, S.-E., Teorell, J., Altman, D., Bernhard, M., Fish, M. S., Cornell, A., Dahlum, S., Gjerløw, H., Glynn, A., Hicken, A., Krusell, J., Lührmann, A., Marquardt, K. L., McMann, K., Mechkova, V., Medzihorsky, J., Olin, M., Paxton, P., Pemstein, D., Pernes, J., Von Römer, J., Seim, B., Sigman, R., Staton, J., Stepanova, N., Sundström, A., Tzelgov, E., Wang, Y.-T., Wig, T., Wilson, S., and Ziblatt, D. (2019). V-Dem Country-Year Dataset 2019.