DATA APPENDIX FOR "STATE NETWORKS AND INTRA-ETHNIC GROUP VARIATION IN THE 2011 SYRIAN UPRISING," COMPARATIVE POLITICAL STUDIES

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I. EVENT CODING

The event data record nine types of actions, coded on a scheme developed inductively from descriptions of events in secondary sources, the newspaper articles themselves, and author interviews with participants and Syrian observers of the uprising. Actions are divided by actor: challenger, regime, regime ally.

Regime actions are as follow:

- (1) *incumbent crowd control*. This tactic captures actions directed at dispersing demonstrators without inflicting high levels of damage on protesters or monitoring them extensively. This category encompasses actions of far more force than one might expect of crowd control in an industrialized democracy. It includes: barricading, non-violently dispersing protests and arresting demonstrators, tear gassing and beating demonstrators, and firing into the air (when doing so causes fewer than two casualties).
- (2) tactical control. This tactic involves an organized form of violence and surveillance directed at a specific segment of a city or town's population, but not the whole town or major neighborhood of a large city. These tactics appear to be geared at separating a contentious population from the rest of the town/city or punishing a specific subset of the city's residents. Examples include: raiding a neighborhood to make arrests, encircling a neighborhood and cutting power and water for several days, storming a neighborhood, opening fire randomly on demonstrations, and using snipers to kill people out demonstrating on the street.
- (3) *town destruction*. These events target entire towns or major neighborhoods of large cities indiscriminately. They inflict heavy damage, either mass property destruction or the killing of 20 or more people. Actions in this category include the siege of entire cities, the shelling of a neighborhood, and the burning of homes.
- (4) *confront*. This tactic describes security or military forces clashing with armed opposition fighters, including formal battles between armed units, skirmishes with defectors, and attacks following an ambush.

Distinctions among the three challenger actions are:

- (1) *non-violent* action, in which a group gathered to make demands on the regime and no violent action was reported;
- (2) *spontaneous violent* action, where crowds initially amassed to demonstrate non-violently and shifted towards the use of violence, such as throwing rocks or beating state allies;
- (3) *coordinated violent* action, involving groups such as "rebels" or "defectors" engaging in coordinated attacks on state forces (the compliment of regime "confront" actions).

Allies are any actors without an official affiliation to the state that act to support the incumbent or harm its challengers. They can take two sorts of actions in the coding scheme: (1) *violent* action or (2) *non-violent* action. When gathered to voice support the state, whether as a counter demonstration or on its own, ally actions count as non-violent. Any sustained physical attack—from throwing stones at and using knives against anti-incumbent demonstrators to organized militias destroying villages supporting challengers—counts as ally violent action.

II. EVENT DATABASE

The event database, collected on the period from February 2011 through August 2012 contains 4424 observations, though only events through December 2011 are analyzed in this article. It follows the structure of Charles Tilly's (1995) dataset on contention in nineteenth-century Great Britain, recording a set of subject-verb-object sequences for actions taken by the state, its challengers and the state's allies. These strings were subsequently fit into the typology described above.

Newspaper-based event data have come under criticism for ignoring events in small and remote locales (selection bias) and for misrepresenting those events they do report (veracity bias) due to the agenda of the newspaper (Ortiz et al., 2005; Weidmann, 2015). Using multiple sources with conflicting agendas helps to addresses veracity bias, as the opposed political agendas of *al-Thawra* and the Syrian Observatory for Human Rights make it highly unlikely that both would miss covering a major event unflattering to the other camp. Using multiple sources required the author to make coding decisions sometimes based upon explicitly contradictory reports. These decisions involved rejecting obvious government fabrications (e.g. when the government shelled the center of Homs, *al-Thawra* claimed that "terrorists are using smoke bombs to make it look like the government is shelling the city center"). In such situations, I consulted of third-party reports, including the scholarly monographs of Jamal Barout (2012) and Azmi Bishara (2013) and the reports of international organizations like Human Rights Watch and Amnesty International. In addition, the coding of events was done in view of all relevant reports to place all potential source biases in view and prevent double-counting of events (Weidmann & Rød, 2015).

There is undoubtedly underreporting of events in small, peripheral locales, but the use of local newspapers makes this far less likely than in datasets based upon major international papers or machine-coding. Whereas the original database (through December 31, 2011) records 2333 events in 436 towns, one leading machine-coded database, GDELT, has observations in 13973 total observations in 97 Syrian towns (Leetaru & Schrodt, 2013; coding rules for transforming this database to the scheme employed here available in replication files). For challenge events in the first year of the uprising—the outcome variable in the present study—the author's database records 973 events in 134 towns, compared to 164 in 32 towns in GDELT; whereas the five towns with the most observations are the site of 30 percent of all observations in the author database, the top five towns account for 57 percent of observations in GDELT. Figure A1 depicts the difference. Finally, selection bias in event recording is also less of a worry when trying to understand the types and sequencing of contention across locales, what Tilly (2002) calls their "internal regularities," than in studies focused on the initial onset of events in a locale.



(a) original database (n=2333)

Figure A1: Comparison of coverage across databases

sub-district (sorted by number of events)

Notes: Each point represents total number of events in the databases for a given sub-district (n=266). Count includes challenger, regime, and ally actions. Databases track events through December 31, 2011.

III. ETHNIC IDENTITY CODING

Ethnic identity variables are taken from the "Syria Town Ethnicity Database," which I constructed jointly with Kheder Khaddour. It is available and described in detail at <u>https://doi.org/10.7910/DVN/YQQ07L</u>.

A national level map plotting the Syria Town Ethnicity data is presented in figure A2; panel (a) plots all towns with equal size, whereas panel (b) plots towns by their built-up area, to indicate relative size of settlements.

One potential objection to the data collection strategy is that interview subjects will generalize from a region's most prominent town being known as a stronghold of a given ethnic group, and simply state that an entire area is populated by that group. The data collection strategy—which entailed choosing interview subjects from the sub-districts for which they provided information, with deep knowledge of their region—was designed to minimize the risk of imputing town identities from those of neighboring towns. Validation against extant sources (discussed in the introduction to the dataset) suggests that this did not occur. Nonetheless, reader might conclude from the nearly-homogeneous ethnic composition of regions like Sweida in figure A2 that coders simply inferred the identity of the whole region from a prominent town or two. Yet this impression reflects, in Sweida, at least, a reality documented by researchers who have conducted sustained on-the-ground research in these areas (ex. Roussel, 2009, p. 6; al-Aballah and al-Hallaq, 2017, ff14).

The considerable town-level heterogeneity appearing in the coding for several other regions known to have diverse populations lends further support to the notion that the coding reasonably reflects town level identity characteristics. The Salamiya region west of Hama, for example, is characterized by such heterogeneity and its diversity is reflected in the data. Figure A3 depicts the diversity recorded in the ethnicity data, and further detail on the historical settlement of this area, consistent with patterns in the database, can be found in work by Darwish (2016, p. 1-5), Orient News (2015, p. 4-11), and Douwes and Lewis (1989, p. 216).

Robustness tests and ethnicity measures

To check the validity of our ethnicity coding, we consulted several extant sources to develop an alternative measure of ethnic identity (described in the document introducing the database, at the above link). This re-coding changed the ethnicity value of 1466 of 5204 towns but, because they were overwhelmingly small villages, these changes affected only five events occurring in five different towns (out of a total of 879 events): four were spillover of violence from neighboring areas into minority towns, and one is a protest in a Sunni town (coded incorrectly in the alternative ethnic database as Christian), al-Bayda, in Tartous governorate.¹

The negative binomial regression is re-fit with these modification to the original coding (table A1, specification 6). The results are statistically and substantively unchanged. These results lend support to the notion that ethnicity is accurately captured in the dataset.

¹ News reports on protests and repression in 2011 (https://www.youtube.com/watch?v=ftSUqIdPEPU) and a 2013 massacre (http://www.telegraph.co.uk/news/worldnews/middleeast/syria/10036680/Syria-Sunni-village-massacred-in-Alawite-heartland.html) confirm the ethnic identity of the town's residents.





(a) all towns equal size



Figure A3: Majority ethnic identity in Hama governorate, by town (built up area)

IV. ALTERNATE SPECIFICATIONS FOR NEGATIVE BINOMIAL REGRESSION

Several alternate indicators for the grievance, opportunity, and local diversity hypotheses are employed in table A1. Specification 1 is the same as specification 3 in table 4 (the most focused test of the rival hypotheses) and later specifications in this table build upon it. To test local diversity hypotheses, *Nearest 10 Alawi* captures the notion of 'encirclement' by measuring the number of the ten closest towns to a given town that have an Alawi majority (specification 2). To test the grievance hypotheses, *Total unemployment* captures the percentage of a town population listed as unemployed in the 2004 census (3), and *Adult illetracy* captures the percentage of a town's adult population characterized as illiterate in the 2004 census (4). To test opportunity theories, *Ruggedness* is a measure of terrain roughness in a 5km radius around a town's center, (calculated from NASA LP DAAC, 2013, specification 5). The alternate ethnicity coding is also included; specification 6 uses the author's coding plus modifications from outside sources. A nightlights measure is also included (specifications 7 and 8, see section IV of the appendix). Finally, as an alternate measure of tribal background, *200mm rain line* is a dummy variable capturing all areas getting less than 200mm of rain per year (taken from Lewis, 1987, specification 9).

Table A2 includes measures of the percentage of a town's population with access to stateprovided water, electricity, and sewage services (taken from the 2004 census).

Finally, to address the risk that the ethnicity coding is systematically biased, table A3 fits the base models, restricting the sample by population size in two ways. First, to address the risk that ethnicity coders simply assigned the ethnic identity of large towns to neighboring small ones—and thereby flattened local diversity—towns with a population smaller than 1000 are excluded (specifications 1-5). Then, to address the risk that major cities' ethnic diversity is driving the result, towns with over 100,000 residents are also excluded (specifications 6-10). The results are substantively the same as in table 4 of the main text.

(S	pecificatio	n 3 in the	text), alte	rnate griev	ance, dive	sity, and e	ethnicity m	leasures	
	(E)	(2)	(3)	(4)	(2)	(9)	(2)	(8)	(6)
Tribes	-1.551^{***} (0.451)	-1.590^{***} (0.454)	-1.891*** (0.375)	-1.523^{***} (0.459)	-1.512^{***} (0.459)	-1.527^{***} (0.451)	-1.551^{***} (0.453)	-1.382^{***} (0.438)	
Government worker	-1.796^{**} (0.849)	-1.709^{**} (0.826)	-2.138** (0.892)	-2.064^{**} (0.856)	-1.863^{**} (0.857)	-1.967^{**} (0.840)	-1.792^{**} (0.856)	-1.879^{**} (0.843)	-1.349^{*} (0.809)
Log(population)	2.046^{***} (0.110)	2.058^{***} (0.110)	2.072^{***} (0.112)	2.012^{***} (0.112)	2.075^{***} (0.111)	2.067^{***} (0.112)	2.045^{***} (0.112)	2.031^{***} (0.110)	2.070^{***} (0.112)
School enrollment	5.209^{**} (2.344)	5.406^{**} (2.329)	6.225^{***} (2.272)	4.773^{*} (2.458)	5.133^{**} (2.376)	5.796^{**} (2.329)	5.205^{**} (2.351)	6.103^{***} (2.319)	3.718 (2.287)
Secondary school	2.294 (1.762)	2.174 (1.765)			2.319 (1.763)	$2.350 \\ (1.750)$	2.283 (1.764)	2.063 (1.754)	6.118^{***} (1.482)
Security base	0.229 (0.276)	0.241 (0.277)	0.263 (0.277)	0.216 (0.277)		0.170 (0.279)	0.230 (0.277)	0.268 (0.274)	0.339 (0.274)
Log(distance to capital)	0.265^{**} (0.129)	0.276^{**} (0.129)	0.235^{*} (0.129)	0.282^{**} (0.129)	0.252^{*} (0.131)	0.278^{**} (0.131)	0.263^{**} (0.131)	0.236^{*} (0.128)	0.248^{*} (0.128)
A-S mix	$0.334 \\ (0.460)$		0.249 (0.454)	0.242 (0.452)	$0.324 \\ (0.467)$	$0.362 \\ (0.463)$	$0.334 \\ (0.462)$	0.070 (0.466)	$0.351 \\ (0.459)$
Nearest 10 Alawi _al		0.018 (0.063)							
Total unemployment			$0.911 \\ (1.450)$						
Adult illiteracy				-2.725 (1.889)					
Terrain ruggedness					0.385 (0.765)				
Nightlights (05-09)							-0.002 (0.042)		
Nightlights (07-09)								-0.077^{**} (0.034)	
200mm rain line									-0.861^{***} (0.275)
Constant	-25.480^{***} (2.151)	-25.671^{***} (2.155)	-24.481^{***} (1.920)	-22.634^{***} (2.145)	-25.555^{***} (2.160)	-26.061^{***} (2.179)	-25.452^{***} (2.199)	-25.932^{***} (2.169)	-27.885^{***} (2.148)
Observations Log Likelihood θ Akaike Inf. Crit.	$\begin{array}{c} 2,755\\ -421.369\\ 0.468^{***} \left(0.081 \right)\\ 860.737\end{array}$	$\begin{array}{c} 2,755\\ -421.585\\ 0.468^{***} \left(0.081 \right)\\ 861.170 \end{array}$	$\begin{array}{c} 2,514\\ -421.820\\ 0.464^{***} \left(0.080 \right)\\ 861.641\end{array}$	$\begin{array}{c} 2,748\\ -421.149\\ 0.470^{***} \left(0.081 \right)\\ 860.298\end{array}$	$\begin{array}{c} 2.755 \\ -421.572 \\ 0.455^{***} \left(0.078 \right) \\ 861.144 \end{array}$	$2,762 -419.724 0.458^{***} (0.079) 857.449$	$\begin{array}{c} 2,751\\ -421.358\\ 0.468^{***} \ (0.081)\\ 862.716\end{array}$	$\begin{array}{c} 2,751\\ -418.977\\ 0.486^{**}\left(0.085\right)\\ 857.954\end{array}$	2,755 -423.508 0.482** (0.085) 865.016
Note:								d. : :r·n>d.	<pre>ru.u>d;cu.u></pre>

		Dependen	at variable:	
		cr	ıcs	
	(1)	(2)	(3)	(4)
Tribes	-1.551^{***}	-1.564^{***}	-1.549^{***}	-1.562^{***}
	(0.451)	(0.452)	(0.455)	(0.454)
Government worker	-1.796^{**}	-1.842^{**}	-1.782^{**}	-1.798^{**}
	(0.849)	(0.851)	(0.862)	(0.851)
Log(population)	2.046***	2.050***	2.043***	2.057***
	(0.110)	(0.111)	(0.120)	(0.115)
School enrollment	5.209**	5.332**	5.153**	5.339**
	(2.344)	(2.356)	(2.351)	(2.375)
Secondary school	2.294	2.371	2.307	2.378
v	(1.762)	(1.763)	(1.826)	(1.783)
Security base	0.229	0.223	0.232	0.228
v	(0.276)	(0.277)	(0.277)	(0.277)
Log(distance to capital)	0.265**	0.261**	0.263**	0.267**
	(0.129)	(0.129)	(0.130)	(0.129)
% resid. w. electricity		-1.748		
		(3.025)		
% resid. w. sanitation			-0.051	
			(0.445)	
% resid. w. water				-0.280
				(0.899)
A-S mix	0.334	0.355	0.345	0.330
	(0.460)	(0.461)	(0.461)	(0.462)
Constant	-25.480^{***}	-23.913^{***}	-25.380^{***}	-25.467^{***}
	(2.151)	(3.381)	(2.214)	(2.146)
Observations	2,755	2,676	2,232	2,568
Log Likelihood	-421.369	-421.160	-421.104	-421.242
θ	0.468^{***} (0.081)	0.468^{***} (0.081)	0.469^{***} (0.081)	0.466^{***} (0.081)
Akaike Inf. Crit.	860.737	862.321	862.208	862.484
Akaike Inf. Crit.	860.737	862.321	862.208 *p<0.1; **µ	862.484 p<0.05; ***p<0

Table A2: Negative binomial of challenger actions, Sunni Arab only February - September 2011 (specification 3 in the text), with public goods measures

observations:			population > 1000				popula	tion >1000 and $<$	100,000	
towns:	all	Sunni	Sunni Arab	Su	nni	all	Sunni	Sunni Arab	Su	nni
time period:		Feb Sept.		Feb Dec.	Oct Dec.		Feb Sept.		Feb Dec.	Oct Dec.
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)	(10)
Tribes	-1.778^{***} (0.444)	-1.712^{***} (0.452)	-1.526^{***} (0.450)	-1.737^{***} (0.412)	-2.149^{***} (0.724)	-1.961^{***} (0.505)	-1.950^{***} (0.525)	-1.699^{***} (0.522)	-1.882^{***} (0.468)	-2.494^{***} (0.885)
Kurdish	0.815 (0.520)	0.904^{*} (0.530)		0.645 (0.496)	-0.788 (0.956)	0.927^{*} (0.544)	0.986^{*} (0.562)		0.750 (0.524)	-0.868 (1.020)
Non-Sunni	-2.231^{***} (0.475)					-2.080^{***} (0.512)				
Government worker	-1.685^{**} (0.804)	-1.890^{**} (0.848)	-1.805^{**} (0.846)	-1.277^{*} (0.753)	0.287 (1.166)	-2.008^{**} (0.846)	-2.291^{**} (0.904)	-2.167^{**} (0.898)	-1.528^{*} (0.793)	0.121 (1.222)
Log(population)	1.995^{***} (0.102)	2.026^{***} (0.106)	2.015^{***} (0.112)	1.898^{***} (0.096)	$\frac{1.451^{***}}{(0.147)}$	2.137^{***} (0.119)	2.163^{***} (0.126)	2.146^{***} (0.130)	2.002^{***} (0.112)	1.487^{***} (0.174)
School enrollment	5.573^{**} (2.213)	4.728^{**} (2.324)	5.263^{**} (2.347)	4.215^{**} (2.089)	1.842 (3.487)	5.571^{**} (2.283)	4.957^{**} (2.420)	5.374^{**} (2.445)	4.368^{**} (2.161)	2.478 (3.593)
Secondary school	0.422 (1.546)	1.240 (1.620)	2.249 (1.764)	0.938 (1.432)	-0.886 (2.262)	-0.033 (1.598)	0.590 (1.689)	1.459 (1.834)	0.450 (1.482)	-1.422 (2.330)
Security base	0.140 (0.267)	0.251 (0.279)	0.235 (0.276)	$0.174 \\ (0.252)$	0.030 (0.404)	$0.121 \\ (0.267)$	0.221 (0.281)	0.207 (0.276)	0.148 (0.254)	0.050 (0.410)
Log(distance to capital)	0.236^{*} (0.123)	0.263^{**} (0.128)	0.256^{**} (0.129)	0.215^{*} (0.122)	-0.034 (0.186)	0.173 (0.153)	0.196 (0.168)	0.147 (0.165)	0.134 (0.158)	0.026 (0.245)
A-S mix	0.691 (0.486)	0.358 (0.471)	0.349 (0.459)	0.110 (0.457)	-2.399^{**} (0.955)	0.839 (0.516)	0.555 (0.503)	0.550 (0.485)	0.289 (0.489)	-35.236 (10,800,359.000)
Constant	-23.592^{***} (1.892)	-24.134^{***} (1.969)	-25.141^{***} (2.169)	-22.038^{***} (1.737)	-15.975^{***} (2.595)	-24.240^{***} (1.969)	-24.682^{***} (2.053)	-25.339^{***} (2.226)	-22.353^{***} (1.798)	-16.413^{***} (2.699)
$\begin{array}{l} & \text{Observations} \\ \text{Log Likelihood} \\ \theta \\ & \text{Akaike Inf. Crit.} \end{array}$	$\begin{array}{c} 2,130\\ -479.239\\ 0.439^{***} \ (0.072)\\ 980.477\end{array}$	$\begin{array}{c} 1,516\\-456.533\\0.433^{***}\ (0.071)\\933.066\end{array}$	$\begin{array}{c} 1,409\\ -420.626\\ 0.471^{***}\ (0.082)\\ 859.253\end{array}$	$\begin{array}{c} 1,516\\-519.988\\0.436^{***}\ (0.069)\\1,059.977\end{array}$	$\begin{array}{c} 1,516\\ -207.363\\ 0.280^{***}\ (0.079)\\ 434.727\end{array}$	$\begin{array}{c} 2,116\\-416.265\\0.476^{***}\ (0.091)\\854.529\end{array}$	$\begin{array}{c} 1,504\\ -395.471\\ 0.448^{***} \ (0.085)\\ 810.942 \end{array}$	$\begin{array}{c} 1,398\\ -364.868\\ 0.502^{***}\left(0.102\right)\\ 747.736\end{array}$	$\begin{array}{c} 1,504\\ -458.779\\ 0.443^{***} \ (0.080)\\ 937.559\end{array}$	$\begin{array}{c} 1,504 \\ -174.603 \\ 0.263^{***} & (0.092) \\ 369.206 \end{array}$
Note:									*p<0.1; **I	o<0.05; ***p<0.01

Table A3: Negative binomial of challenger actions, restricted by population size

V. NIGHTLIGHTS

De Juan and Bank (2015) offer an additional alternate explanation incorporating both marginalization and state linkage elements. They argue that short-run change in patronage ties—operationalized as the areas that experienced power cuts during periods of electricity grid load shedding and measured through satellite measure of nightlight emissions —explains patterns of contention. The results of that study differ from those presented here for several reasons.

First, nightlight fluctuation does not capture dynamics of state linkage or patronage in Syria. Whereas the unequal distribution of state jobs is a regular and well-documented grievance cited by revolution participants, there is no evidence to suggest that load shedding was viewed in a similar way; complaints in local newspapers described it only as bias towards urban centers (ex. al-Bunni, 2009). The available statistical evidence suggests that this perception reflected reality, with urban centers spared the greatest cuts, but for reasons largely unrelated to clientelism. Regime clients outside the center of the center of Damascus, for example, in the spontaneous Alawi suburb of Mezze 86 and Dahiet Qudsayya (a suburb heavily populated by state employees), received power cuts. Meanwhile, the historically Sunni and oppositional old core of Lattakia did not see cuts—under the justification of "supporting tourism"—while other areas of this heavily Alawi governorate faced cuts (al-Bunni, 2009). This city-center bias in load shedding was the same in all other regions of country (personal correspondence with Ali Hamzeh, Professor of Electrical Engineering at Al Ahliyya Amman University, Jordan, September 16, 2017).

Second, nightlights measures for the Alawi heartland raise further questions about the relationship between nightlight emissions and patronage; the drop in nightlight emissions in the coastal provinces is dramatic and stands at odds with all other data on patronage, which indicate heavy favoritism of this area. Eight of the top 10 and 15 of the top 20 sub-districts losing nightlights from 2007 to 2009 (the period examined in De Juan and Bank, 2015) are in Lattakia or Tartous governorates. Al-Qardaha, the hometown of al-Asad family, was the eighth-largest loser of 261 total sub-districts. Moreover, a regression of nightlight change on town characteristics shows that Alawi areas lose the most nightlight, and governorate capitals are the least affected (see table A4).

The Alawi bias in loss of nightlights suggests that one of several phenomena is at work: extreme self-sacrifice on the part of the regime, population movement, or measurement error. The first possibility is highly implausible, as is inconsistent with all available qualitative evidence. The second, is consistent with the mass out-migration from rural Alawi areas to the periphery of major cities documented by Balanche (2016), though it is unclear that a two-year measurement difference would be sufficient to capture this change statistically. The most plausible explanation for the drop in coastal nightlight emissions is measurement error. Contrary to De Juan and Bank's supposition (2015: 95ff3), trends in power consumption over time consistently rise while nightlight emissions fall between 2007 and 2009. Specifically, while night light emissions *decreased* 20 percent, actual electricity consumption *increased* 10 percent (see table A5). Measurement error introduced by urban light saturation and satellite instrument fluctuation across years is compounded by aggregation over large territorial units, like the Syrian sub-districts employed in this study (Hsu et al., 2015, p. 1865-1869).

Third, De Juan and Bank's (2015) operationalization of their dependent variable measures violence in civil war, while the underlying theoretical concept is violent challenge giving way to civil war onset; when the dependent variable is re-measured to better fit this concept, the results do not support their conclusions. The main empirical test in De Juan and Bank's (2015) article is a logistic regression of whether 25 or more deaths occurred in a sub-district from the beginning of the uprising until November 1, 2012. Eighty-six percent of the deaths in this database occur after January 1, 2012, under civil war conditions. For the reasons elaborated by Kalyvas (2006) and discussed in the article's main text (in the "Quantitative Analysis of Mobilization" section), including the civil war period introduces a form of 'post-treatment bias' to any attempt to assess the

role of pre-conflict patronage structures on propensity for challenge. Only 36 of the 72 sub-districts coded by De Juan and Bank (2015) as '1's on the outcome variable would still be coded this way if the time period were halted at January 1, 2012, and only 26 if halted at October 1, 2011. When these shorter periods are employed, the result does not hold (see table A6).

Finally, the main independent variable is measured for too short a time period, after the 'treatment' of load shedding has already commenced. Load shedding began in 2006, jumping from 55 GwH in 2005 to 345 GwH in 2006 to 427 GwH in 2007 (Beides et al., 2009, 27). When the time period for nightlight comparison is moved back to before load shedding began in earnest, from 2005 to 2009, this variable has no statistically significant effect in the model fit by the authors (see table A6). The extreme fluctuation in satellite measures between 2006 and 2008 (see table A7) is a likely cause for the anomalous finding.

Table A4: Determinants of nightlights change,
OLS regression of change in annual DSMP-OLS average.
Unit of analysis: town.

DV:		cha	nge 2004 to 2	2009			cha	nge 2007 to :	2009	
observations:		all		coast	only		all		coast	only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log(\text{population})$	$\begin{array}{c} -0.324^{***} \\ (0.038) \end{array}$	-0.645^{***} (0.088)	$\begin{array}{c} -0.243^{***} \\ (0.094) \end{array}$	-0.284^{***} (0.107)	-0.089 (0.191)	-0.667^{***} (0.040)	-0.513^{***} (0.098)	-0.314^{***} (0.106)	-0.318^{**} (0.144)	-0.135 (0.258)
% resid. with electr.		2.893 (1.889)	2.804 (1.874)		7.925 (6.879)		-1.361 (2.117)	-1.382 (2.128)		5.013 (9.287)
% resid. with sewers.		-1.280^{***} (0.240)	-1.154^{***} (0.240)		-1.111^{**} (0.460)		-1.168^{***} (0.269)	-1.208^{***} (0.272)		-0.874 (0.620)
% wkfc. gov. wr kr	-0.391^{**} (0.196)	2.106^{***} (0.684)	$\frac{1.926^{***}}{(0.679)}$	-2.716^{***} (0.398)	2.436^{*} (1.349)	-1.321^{***} (0.206)	-0.712 (0.767)	-0.839 (0.771)	-4.246^{***} (0.537)	-0.217 (1.822)
road density	-0.014 (0.164)	-0.209 (0.334)	-0.221 (0.331)	-1.922^{***} (0.404)	-2.172^{***} (0.678)	-1.588^{***} (0.172)	-2.220^{***} (0.374)	-2.168^{***} (0.376)	-3.513^{***} (0.545)	-4.811^{***} (0.916)
terr. ruggedness	-2.023^{***} (0.260)	-2.611^{***} (0.483)	-2.170^{***} (0.483)	1.760^{***} (0.488)	$\begin{array}{c} 0.641 \\ (0.859) \end{array}$	-1.622^{***} (0.274)	-1.803^{***} (0.542)	-1.647^{***} (0.549)	4.735^{***} (0.658)	3.969^{***} (1.160)
% wkfc. mid. class		-4.161^{***} (1.122)	-3.663^{***} (1.113)		-7.471^{***} (2.184)		0.279 (1.258)	$0.589 \\ (1.264)$		-6.719^{**} (2.949)
% w. univ. educ.		-1.732 (4.840)	-0.146 (4.795)		9.795 (7.928)		-9.302^{*} (5.424)	-7.931 (5.448)		18.910^{*} (10.704)
Alawi maj. (binary)	-1.014^{***} (0.136)	-1.780^{***} (0.261)	-1.627^{***} (0.259)	-0.449 (0.293)	-0.506 (0.471)	-1.169^{***} (0.143)	-1.187^{***} (0.292)	-1.111^{***} (0.294)	-0.079 (0.395)	-0.603 (0.636)
tribal Sunni maj.		-0.908^{***} (0.273)	-0.654^{**} (0.272)				-1.334^{***} (0.305)	-1.224^{***} (0.309)		
Kurdish maj.		-1.122^{**} (0.436)	-0.776^{*} (0.435)				-0.886^{*} (0.489)	-0.762 (0.494)		
Other minority maj.		-1.887^{***} (0.271)	-1.705^{***} (0.270)				-0.033 (0.304)	$\begin{array}{c} 0.027\\ (0.307) \end{array}$		
Governorate capital	1.491^{*} (0.882)	3.937^{***} (0.981)		1.417 (1.992)	1.421 (2.233)	$\begin{array}{c} 4.172^{***} \\ (0.926) \end{array}$	$\begin{array}{c} 4.719^{***} \\ (1.100) \end{array}$		3.829 (2.684)	$3.380 \\ (3.015)$
Sub-dist capital			-1.685^{***} (0.264)					-0.359 (0.300)		
Constant	$\frac{1.918^{***}}{(0.263)}$	3.350^{*} (1.965)	$\begin{array}{c} 0.172\\ (1.966) \end{array}$	1.583^{*} (0.856)	-6.824 (6.990)	3.544^{***} (0.276)	4.621^{**} (2.202)	2.994 (2.233)	-0.561 (1.153)	-5.226 (9.437)
Observations R ² Adjusted R ²	4,811 0.076 0.075	1,529 0.170 0.163	$\begin{array}{c} 1,529 \\ 0.184 \\ 0.177 \end{array}$	852 0.131 0.125	348 0.131 0.105	4,811 0.180 0.179	1,529 0.128 0.120	1,529 0.118 0.110	852 0.186 0.181	348 0.190 0.166

L1B 2014, road density from UN OCHA 2010, ethnic majority variables from author database.

year	tot. output	domestic	anuual	peak daily	nightlight	nightlight	anuual
	(gwh)	consump. (gwh)	pct. chg.	supply (MW)	total	mean	pct. chg.
2004					1022650	3.82	
2005	34935	34093		6008	894502	3.34	-14.3
2006	37504	36923	7.7	6739	1121711	4.19	20.3
2007	38642	40560	9.0	7007	1181902	4.42	5.1
2008	41023	42022	3.5	6715	1011711	3.78	-16.8
2009	42308	44521	5.6	7223	945193	3.53	-7.0
2010	46413	47232	5.7	8024			

Table A5: National-level night lights and electricity statistics

Sources: Electricity supply and consumption figures from Syrian Electricity Ministry Annual Reports, 2006-2011. Nightlights data from NOAA (2013), DSMP-OLS, 2004-2009.

End time period:	Nov. 12		Jan. 12		Oct	. 11
Deaths threshold:		25		10	25	10
	(1)	(2)	(3)	(4)	(5)	(6)
sc_emplgov	-0.012 (0.021)	-0.052^{*} (0.028)	-0.053^{**} (0.021)	-0.027 (0.017)	-0.027 (0.024)	-0.016 (0.020)
sunni	$\begin{array}{c} 0.369 \\ (0.742) \end{array}$	-0.031 (1.203)	$0.969 \\ (0.746)$	$\begin{array}{c} 0.946 \\ (0.594) \end{array}$	$1.062 \\ (0.871)$	$0.694 \\ (0.669)$
alawites	-0.022 (1.055)	$\begin{array}{c} 0.347 \\ (1.454) \end{array}$	$0.947 \\ (0.726)$	$0.925 \\ (0.622)$	2.079^{**} (0.813)	1.732^{**} (0.724)
sc_enroll611	-0.046 (0.169)	-0.340 (0.293)	$\begin{array}{c} 0.349 \\ (0.267) \end{array}$	0.301^{*} (0.176)	$\begin{array}{c} 0.074\\ (0.262) \end{array}$	$0.240 \\ (0.257)$
log_border_dist	-0.003 (0.321)	1.180^{*} (0.610)	$\begin{array}{c} 0.399 \\ (0.347) \end{array}$	$0.096 \\ (0.264)$	-0.125 (0.379)	-0.086 (0.314)
share_urban_2004	$\begin{array}{c} 2.932^{***} \\ (0.992) \end{array}$	2.528^{**} (1.284)	2.378^{**} (1.030)	$2.714^{***} \\ (0.882)$	2.424^{*} (1.253)	3.353^{***} (1.076)
sc_electricity	-0.008 (0.112)	0.855^{**} (0.414)	0.457^{*} (0.254)	-0.049 (0.079)	$\begin{array}{c} 0.348 \\ (0.293) \end{array}$	$\begin{array}{c} 0.043\\ (0.196) \end{array}$
sc_malunempl	-0.009 (0.055)	$0.092 \\ (0.082)$	$\begin{array}{c} 0.013 \\ (0.048) \end{array}$	-0.006 (0.040)	-0.079 (0.073)	-0.087 (0.062)
road_density	-2.590^{**} (1.250)	-0.223 (1.415)	$0.256 \\ (0.921)$	-0.089 (0.932)	-0.455 (0.973)	0.111 (0.997)
log_pop_2004	$\frac{1.932^{***}}{(0.465)}$	3.094^{***} (0.832)	$\frac{1.205^{***}}{(0.392)}$	$\begin{array}{c} 1.005^{***} \\ (0.334) \end{array}$	$\frac{1.245^{***}}{(0.426)}$	1.051^{***} (0.374)
ligmean_change_0907	-0.464^{***} (0.151)	-0.276 (0.194)	-0.120 (0.126)	-0.168 (0.110)	-0.175 (0.136)	-0.159 (0.126)
Constant			-96.017^{***} (34.322)	-38.716^{**} (17.460)	-57.662 (35.491)	-41.790 (28.214)
Observations FE Log Likelihood Akaiko Inf. Crit	260 Y -65.355 178 700	260 Y -36.479	260 N -60.422	260 N -80.725 185.450	260 N -48.048	260 N -60.762
Note:	110.109	120.909	144.040	*p<0.1	; **p<0.05;	***p<0.01

Table A6: Replication of DeJuan and Bank (2015) with alternate outcome variablespecifications. Unit of analysis: sub-district.

Specification (1) is the exact model fit by De Juan and Bank (2015). It separates (on two governorates) due to the fixed effects, so fixed effects are not used in specifications (3) through (6). When fixed effects are included, separation occurs on 4 governorates in specification (4), 5 on (5), 4 on (6).

Table A7: Replication of DeJuan and Bank (2015) with alternate nightlight years. Logistic regression of > 25 deaths, Feb. 2011 - Nov. 2012. Unit of analysis: sub-district.

	(1)	(2)	(3)	(4)	(5)	(6)
sc_emplgov	-0.012 (0.021)	-0.009 (0.020)	-0.007 (0.020)	-0.009 (0.020)	-0.008 (0.021)	-0.010 (0.020)
sunni	$0.369 \\ (0.742)$	$\begin{array}{c} 0.416 \\ (0.699) \end{array}$	$\begin{array}{c} 0.400 \\ (0.695) \end{array}$	$\begin{array}{c} 0.367 \\ (0.728) \end{array}$	$0.359 \\ (0.741)$	0.324 (0.713)
alawites	-0.022 (1.055)	-0.001 (0.958)	-0.025 (0.957)	-0.037 (1.024)	-0.012 (1.037)	-0.067 (1.002)
sc_enroll611	-0.046 (0.169)	$\begin{array}{c} 0.033 \\ (0.165) \end{array}$	$0.037 \\ (0.166)$	-0.017 (0.168)	-0.055 (0.170)	$0.008 \\ (0.170)$
log_border_dist	-0.003 (0.321)	-0.203 (0.306)	-0.180 (0.306)	-0.026 (0.315)	-0.068 (0.316)	-0.161 (0.306)
share_urban_2004	$2.932^{***} \\ (0.992)$	2.427^{**} (0.955)	2.362^{**} (0.956)	$2.659^{***} \\ (0.965)$	$2.876^{***} \\ (0.982)$	$2.554^{***} \\ (0.957)$
sc_electricity	-0.008 (0.112)	$\begin{array}{c} 0.013 \\ (0.118) \end{array}$	$\begin{array}{c} 0.021\\ (0.124) \end{array}$	0.003 (0.115)	-0.010 (0.110)	$\begin{array}{c} 0.013 \\ (0.119) \end{array}$
sc_malunempl	-0.009 (0.055)	$\begin{array}{c} 0.001 \\ (0.051) \end{array}$	$\begin{array}{c} 0.001 \\ (0.050) \end{array}$	-0.002 (0.053)	-0.006 (0.054)	-0.0002 (0.053)
road_density	-2.590^{**} (1.250)	-2.186^{**} (1.107)	-2.276^{**} (1.117)	-2.484^{**} (1.190)	-2.665^{**} (1.261)	-2.615^{**} (1.196)
log_pop_2004	$\frac{1.932^{***}}{(0.465)}$	2.055^{***} (0.470)	$2.094^{***} \\ (0.474)$	2.016^{***} (0.468)	$\frac{1.925^{***}}{(0.466)}$	2.098^{***} (0.470)
ligmean_change_0907	-0.464^{***} (0.151)					
d0904		-0.075 (0.187)				
d0905			-0.142 (0.187)			
d0906				-0.360^{**} (0.142)		
d0907					-0.448^{***} (0.157)	
d0908						-0.547^{**} (0.243)
Observations Log Likelihood Akaike Inf. Crit.	$260 \\ -65.355 \\ 178.709$	$260 \\ -70.577 \\ 189.155$	$260 \\ -70.364 \\ 188.727$	$260 \\ -67.263 \\ 182.526$	$260 \\ -66.284 \\ 180.569$	$260 \\ -68.076 \\ 184.153$
Note:				*p<0).1; **p<0.05;	***p<0.01

Specification (1) is the exact model fit by De Juan and Bank (2015). Nightlights data for specifications (2) through (6) from NOAA (2013).

ADDITIONAL REFERENCES

- al-Abdallah, A., & al-Hallaq, A. A. (2017, July 15). Duruz Suriya [The Druze of Syria]. *Al-Jumhuriya*. Retrieved from <u>http://aljumhuriya.net/36883</u>
- al-Bunni, Y. (2009, August 12). Taqnin al-kahraba' bayn al-'ashwa'iyya wa-ina'dam al-halul altaqnin idhlal li-l-mawatin akthar min ma huwwa khutta li-tawfir al-taqa [Electricity load shedding between randomness and lack of solutions: humiliation of citizens more than a plan to distribute electricity]. *Kassioun*. Retrieved from http://wwe.kassiounpaper.com/syria/item/28678-2016-11-30-00-57-08
- Balanche, F. (2016). "Go to Damascus, my son": Alawi demographic shifts under Ba'ath Party rule. In M. Kerr & C. Larkin (Eds.), *The Alawis of Syria: war, faith and politics in the Levant* (pp. 78–106). New York: Oxford University Press.
- Beides, H., Covindassamy, A., Alshraih, W., Busz, H., & Boukantar, K. (2009). Syrian Arab Republic Electricity Sector Strategy Note (No. 49923–SY). World Bank Energy Sector Management Assistance Program (ESMAP). Retrieved from <u>https://openknowledge.worldbank.org/handle/10986/18896</u>
- Douwes, D., & Lewis, N. N. (1989). The Trials of Syrian Isma ilis in the First Decade of the 20th Century. *International Journal of Middle East Studies*, 21(2), 215–232.
- Hsu, F.-C., Baugh, K. E., Ghosh, T., Zhizhin, M., & Elvidge, C. D. (2015). DMSP-OLS Radiance Calibrated Nighttime Lights Time Series with Intercalibration. *Remote Sensing*, 7(2), 1855– 1876.
- Leetaru, K., & Schrodt, P. (2013). GDELT: Global Data on Events, Language, and Tone, 1979-2012. Presented at the International Studies Association Annual Conference, San Diego, CA. Retrieved from http://gdelt.utdallas.edu/about.html
- Lewis, N. N. (1987). *Nomads and Settlers in Syria and Jordan, 1800-1980*. New York: Cambridge University Press.
- NASA Land Processes Distributed Active Archive Center (LP DAAC). (2013). ASTER L1B. USGS/Earth Resources Observation and Science (EROS) Center. Retrieved from https://lpdaac.usgs.gov
- National Oceanic and Atmospheric Administration. (2013). Version 4 DMSP-OLS Nighttime Lights Time Series. Retrieved from <u>http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html</u>
- Orient News. (2015). *al-Isma 'iliun fil-thawra al-suriyya*... [Isma 'ilis in the Syrian revolution...] (Orient Vision for Research and Studies). Retrieved from <u>http://orient-news.net/ar/news_show/92777/0/</u>الإسماعيليون-في-الثورة-السورية/0/
- Ortiz, D., Myers, D., Walls, E., & Diaz, M.-E. (2005). Where Do We Stand with Newspaper Data? *Mobilization: An International Quarterly*, *10*(3), 397–419.
- Roussel, C. (2009). La frontière communautaire entre druzes et sunnites en Syrie. Une fragmentation socio-spatiale instrumentée par le pouvoir politique. *EchoGéo*, (8).

- Syrian Electricity Ministry. (2006, 2011). al-Taqrir al-ihsa'i al-sanawi [Annual statistical report]. Retrieved from http://www.moe.gov.sy/userfiles/file/Statistical%20reports/reports_2006.pdf
- Tilly, C. (1995). *Popular Contention in Great Britain, 1758-1834*. Cambridge, Mass: Harvard University Press.
- Tilly, C. (2002). Event Catalogs as Theories. Sociological Theory, 20(2), 248–254.
- UN Office for the Coordination of Humanitarian Assistance. (2017, June 1). OCHA's Common Operational Datasets for Syria. Retrieved from https://data.humdata.org/dataset/syrian-arabrepublic-administrative-boundaries-populated-places
- Weidmann, N. B. (2015). On the Accuracy of Media-based Conflict Event Data. *Journal of Conflict Resolution*, 59(6), 1129–1149.
- Weidmann, N. B., & Rød, E. G. (2015). Making uncertainty explicit Separating reports and events in the coding of violence and contention. *Journal of Peace Research*, *52*(1), 125–128.