The Web of War:
A Network Analysis of the Spread of Civil Wars in Africa*

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ABSTRACT

War is typically studied by treating states as independent data points, focusing on particular characteristics and risk factors of individual states as causes of conflict. This situation is ironic, because it is the *interactions* among states in the international system that forms the entire unpinning of international relations theory. The world's states and the relationships between them would therefore be better modeled as a *network*. Network analysis (graph theory), which has been extensively developed and tested in the natural sciences (e.g. ecological networks and food webs), can be used to examine the structure and behavior of the international system as a whole, allowing the quantification and analysis of: (1) how individual state behavior affects and is affected by the state system; (2) the role of indirect interactions (via linked neighbors), which are otherwise hard to study; and (3) the influence of "key player" states in the network (i.e. if and how certain states exert a disproportionate influence on the state system). Network analysis lends itself particularly well to the question of whether transnational factors are causes of civil war in neighboring states. Using data on civil wars in Africa from 1946-2002, we find that civil wars are positively (though weakly) related to states with greater topological importance in the network, even when controlling for other established causes of war.

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INTRODUCTION

> "In most cases, our first instinct is to explain behavior in terms of the actors' preferences and power. Instead, we should start with how the actors are positioned."
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> —Robert Jervis (1997), *System Effects*

Causes of war are typically studied by examining correlates of the warring states themselves—such as their political, military, economic, or social characteristics (Bennett and Stam 2004; Vasquez 1993; Vasquez 2000). However, this is a strange perspective to take given that international relations is, both by definition and by theoretical underpinnings, the result of *interactions* between numerous states in a complex international *system* (Jervis 1997; Waltz 1979). Understanding the behavior of units in an interconnected system demands a different approach, an approach that goes beyond the attributes of individual states, to one that examines the occurrence of war as a phenomenon within the *network* of states.[3]

A network approach is likely to be important to international relations, because the spread of conflict across national borders is not only common, but can have massive knock-on consequences, sparking violence across entire regions or continents. The assassination of Archduke Franz Ferdinand in Sarajevo in 1914, for example, was essentially an act of rebellion against the Austro-Hungarian government—a local dispute (Mombauer 2002; Strachan 2004). However, it quickly spread throughout the Balkans, the Empire, Europe and the world. Interestingly, both the causes and the consequences of Vienna's decision to crack down on Serbia stem from interconnections among the local network of states and nations. In Hungary, for example, the ruling Magyar minority faced the prospect of rebellion from rival groups should the Serbian nationalist cause go unpunished in the Balkans. Austria-Hungary was therefore determined to crush Serbia. Once war began, the vast web of complex political, diplomatic, and geographical interconnections between the European great powers meant that, within the space of a few weeks, the entire European continent, as well as numerous other regions around the world, was engulfed in a war in which millions would die.

World War I is often cited as bizarre event: how could such a seemingly local affair spread to enflame a major international conflict? However, this phenomenon of conflict contagion is perhaps the norm rather than the exception. Wars throughout history have tended to accumulate increasing numbers of protagonists, allies, and enemies as time goes on—as various factions begin to see the necessity of taking sides, or the opportunity to reap the spoils of war. What is bizarre is that the quantitative study of war has tended to ignore the role of interconnections in the causes of conflict.

Although the spread of conflict is likely to be a complex phenomenon, it is not random. Conflict spreads because of specific types of linkages between neighboring

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[3] Such an approach finds roots in a number of disciplines where behavior is modeled as a function of both the unit of interest *and* its environment, in particular Kurt Lewin's "field theory" in sociology (Cartwright 1964; Lewin 1951).

countries, such as transborder groups with common grievances, access to arms, or shared resources. In order to understand the process of conflict contagion, therefore, we would be well advised to apply the quantitative methods most relevant to understanding interconnections: network analysis (i.e. the application of graph theory). Although there were some initial forays into the role of graph theory in international relations (Harary 1961), it has remained almost totally unexplored since (for a review see Maoz et al. 2005). Only recently, work by Zeev Maoz and colleagues have begun to systematically use the tools of network analysis to examine international politics and inter-state wars (Maoz 2006; Maoz et al. 2006; Maoz et al. 2007). One initial prediction from a network perspective is that, as in structural realism, a state's context is more important than its content. However, a network approach does not rule this out, and in fact offers a novel way to test the alternative: unusual state characteristics, ideologies, or policies can be modeled in terms of their impact on the network as a whole.

In this paper, we focus on civil wars. Compared to inter-state wars since 1945, civil wars have been more frequent, killed more people, presented more problems (refugees, poverty, disease), and are less well studied and understood (Fearon and Laitin 2003). Furthermore, civil wars are a good test case for network analyses, because they are often fought by factions or groups that span national borders—especially in Africa, where colonial boundaries often bear little resemblance to the ethnic divisions on the ground (Blanton, Mason, and Athow 2001).

Numerous political scientists, historians and policymakers have noted the important effects of regional factors in the spread of civil conflict (Cederman 2002; Ross 2006; Toft 2003; Vasquez 1993; Vasquez 2000). Nevertheless, the quantitative study of civil war has remained rigidly focused on what characteristics of individual states make them more or less prone to civil war. Amazingly, it was not until this year that Gleditsch (2007) published the first quantitative study to show that transnational factors—influences from neighboring states—increase the probability of civil wars. As he noted, "the risk of civil war is not determined just by a country's internal or domestic characteristics, but differs fundamentally, depending on a country's linkages to other states" (Gleditsch 2007, 293). His article "clearly suggests that transnational factors exert important influences on the risk of civil war onset and provides a stepping stone for future research of this kind" (Gleditsch 2007: 306). As Gleditsch noted, there were several limitations of his study. In particular, Gleditsch only looked at immediate neighbors (with a network approach, we can look at 2nd and 3rd order neighbor effects). Second, neighbors were defined simply as those within 950km of each other (with a network approach, we can be much more specific and examine precise interconnections without any arbitrary definitions).

A Short History of Networks

In hierarchical systems, interacting parts form a whole and these two levels of organization (the parts and the whole) mutually influence each other. The behavior of the parts is constrained by the whole, and the dynamics of the whole is a consequence of that of the parts. In order to describe and better understand such systems, we need to model them as "graphs" and study them using the techniques of network analysis. A graph represents the relation between a set of nodes (e.g. states) and a set of links (e.g. country borders). The nature of the relation reflects the actual problem at hand (for example, if we aim to understand the dynamics of a social group of classmates, the relation can be defined as “friendship”, and links can be drawn between nodes representing friends). Graph theory is a relatively young science, and was not formalized until the work of Hungarian mathematicians Paul Erdos and Albert Rényi in the mid 20th century (Graham and Nesetril 1997). It had already been applied in many fields of science before Harary first applied it to political issues in the 1950s and 60s (Harary 1961). Recently, thanks to information technology, we are able to handle huge data bases and analyse the “topology” (what is connected to what) of large and complex systems, often revealing important and previously hidden properties of hierarchical systems, such as “small-world” phenomena (Watts and Strogatz 1998) and the role of network hubs (Barabási 2003).

The basic models of networks have been extensively applied to numerous areas of research ranging from terrorist networks, to transportation infrastructure, to the internet, to cooperation (Jordán In press; Nowak 2006). One of the areas in which network analysis has found a natural home is in the life sciences where, as Darwin so eloquently described, everything from molecules to organisms to ecosystems are interconnected in a vast network of interacting entities. Every aspect of competition, survival, and reproduction is shaped by the push and pull of the tangled web of nature. Not surprisingly, therefore, some of the most important insights, experiments, and theories have emerged from the life sciences.

Insights from the Life Sciences

Network analysis has become a well-established and indispensable tool to explore the interactions between coexisting species in ecosystems. There is a host of cases in which the behavior of individual species is influenced by the community—or the reverse, where community dynamics is modified by a single disturbed species. This clearly has parallels with international relations, in which individual states are heavily influenced by the community of nations (Waltz 1979), and yet the community of nations can be severely altered by a single revisionist or failed state (e.g. Germany in 1939, Sudan in 2007). We may therefore look to biology for tools, insights and predictions on how the dynamics of networks influence individual-community interactions, as well as for specific methodologies that have been developed to analyze such networks and to derive policy recommendations for intervention.

Ecologists recognized long ago (in the 1920s) the significance of *indirect* interactions within complex networks. We now have examples of important biological effects that are caused by species 7- or 8-steps distant, and examples of indirect effects between two species that are stronger (via other connected species) than even their direct (dyadic) interactions. The “enemy of my enemy is my friend” situation is a textbook example of indirect effects between species, known as a “trophic cascade”. For example, rabbits in Donana National Park benefit from their own predator, the lynx, because the lynx also feed on their other natural enemies. This causes a stronger, positive indirect effect (reducing competitors and other predators) than a weaker, negative direct one (predation). Indirect effects become even more important if the network of interactions is damaged: in over-fished marine systems, for example, certain species begin to exhibit strange behavior due to altered control regimes, and may pave the way for invasions of other species. Invasive species become increasingly dangerous as habitats are altered. The explosion of Zebra Mussels in the North American Great Lakes, brought about by industrial pollution, wrought massive financial costs on water management systems.

Such subtle round-about relationships were essentially invisible, or just appeared as noise, before the advent of network analysis provided methods to reveal the intricate patterns of interaction. It is possible—even likely—that complex, indirect interactions among states has not only been unexplored, but have actually misled or misinformed previous studies of international relations (Jervis 1997; Maoz et al. 2005). Certainly, the general rule has been to ignore them in quantitative studies.

Finally, the life sciences offer examples of the fragmentation of spatial ecological networks ("landscape patchworks"), resulting in changes in the structure of local interaction networks (as we build highways, for example, the prairies becomes fragmented, coyotes disappear from small fragments, wild cats and foxes start to bloom, predating small birds to extinction). Such unforeseen (and often unforeseeable, without network analysis) consequences of interfering with network structure also suggests parallels with the complexity of international relations: failed states, or interventions in a particular state may generate a series of significant but complex knock-on effects that ripple through the system (Jervis 1997). Another important problem is that small changes in ecological networks are typically followed by reorganization processes (resilience is a general property of ecosystems), which is analogous to shifts in the balance of power as states rise or fall (Cederman 1997; Turchin 2005). All in all, the coexistence and competition among species in complex ecosystems raises questions that are strikingly similar to those raised in international relations. What is notable is that ecologists are well ahead of political scientists in terms of analyzing, understanding, and solving problems inherent in network dynamics.

On the basis of this converging literature from the life sciences and international relations, we propose to test a very simple hypothesis: civil wars are more likely to occur in states that have a high level of network connectivity (because this exposes them to a higher frequency and diversity of destabilizing influences from elsewhere in the network).

METHODS

We limit our analysis to civil wars on the African continent (in subsequent analyses we are examining the whole world). Africa accounts for a significant proportion of the world's civil wars, despite dire economic and social conditions which magnify the human costs of these wars. For example, Africa has 8 of the world's 10 "most vulnerable" states according to the latest Failed States Index (Foreign Policy/Fund for Peace 2007). The variables we used in our analysis are given in Table 1 and described below.

Table 1. Variables used in the analysis, for each country on the African continent.

Label	Variable Description	Transform-ations	Source
CIVIL WAR	Proportion of civil war years*	-	Calculated from Gleditsch (2007)
INT WAR	Proportion of inter-state war years**	-	Calculated from Gleditsch (2007)
D	Links to immediate neighbors	-	This study
TI^1	Topological Importance with respect to neighbors	-	This study
TI^2	Topological Importance with respect to second-neighbors	-	This study
POLITY	Democracy	-	(Gleditsch 2007)
ETHNIC	Ethnic dispersion	-	(Gleditsch 2007)
POPLN	Population	Ln	(Gleditsch 2007)
GDP	Gross Domestic Product	Ln	(Gleditsch 2007)

* Number of years of civil war / number of years in database since 1946.

** Number of years of interstate war / number of years in database since 1946.

Conflict Data

We use Gelditsch's (2007) replication dataset on civil wars from the Uppsala/PRIO armed conflict data project (African countries only).[4] Wars were defined as armed conflict between 1946-2002 in which 25 or more people were killed per year (as Gleditsch notes, higher thresholds presented problems for earlier analyses, such as lulls in fighting being coded as the end of/restarting of an ongoing war). Our dependent variable was the *proportion* of years that each country experienced civil war since 1946 (the precise time period varies depending on when countries enter the dataset as independent states).[5] In our analyses we check results with some alternative versions of the dependent variable.

Country-Specific Data

Country-specific data also come from the Gleditsch (2007) dataset (Table 1): (1) *GDP* is measured in constant 1985 US dollars, and is transformed to its natural logarithm given that an increase in one dollar is expected to matter more when states are relatively poor (Gleditsch 2002); (2) *Democracy* is measured according to the standard Polity scale, ranging from –10 (less democratic) to 10 (more democratic); (3) *Ethnic dispersion* is coded as the share of the population not in the dominant ethnic group, coded as 100 minus the percentage share of the largest ethnic group (based on data from Vanhanen 2001). Higher values indicate a more heterogeneous ethnic composition; (4) *Population* is the natural log of the total population size (based on data from Gleditsch 2002). Each of these four variables was averaged over all years for each country.

Network Data

Using standard network software (UCINET, Borgatti, Everett, and Freeman 2002), we constructed a network graph (Figure 1) of all countries on the African continent (excluding islands, e.g. Madagascar, Zanzibar). The "nodes" in the graph represent countries, and the links represent common borders (of any length) with neighboring countries. Thus, in the present paper we emphasize the role of being a neighboring state in direct contact and do not consider any other aspect of geography (such as distance between capitals, or border terrain). The orientation in Figure 1 is arbitrary (it is constructed so as to minimize space and maximize clarity). Therefore, this network, representing only neighborhood relations (i.e. topology), does not overlay directly onto a standard geographical map (Figure 2).

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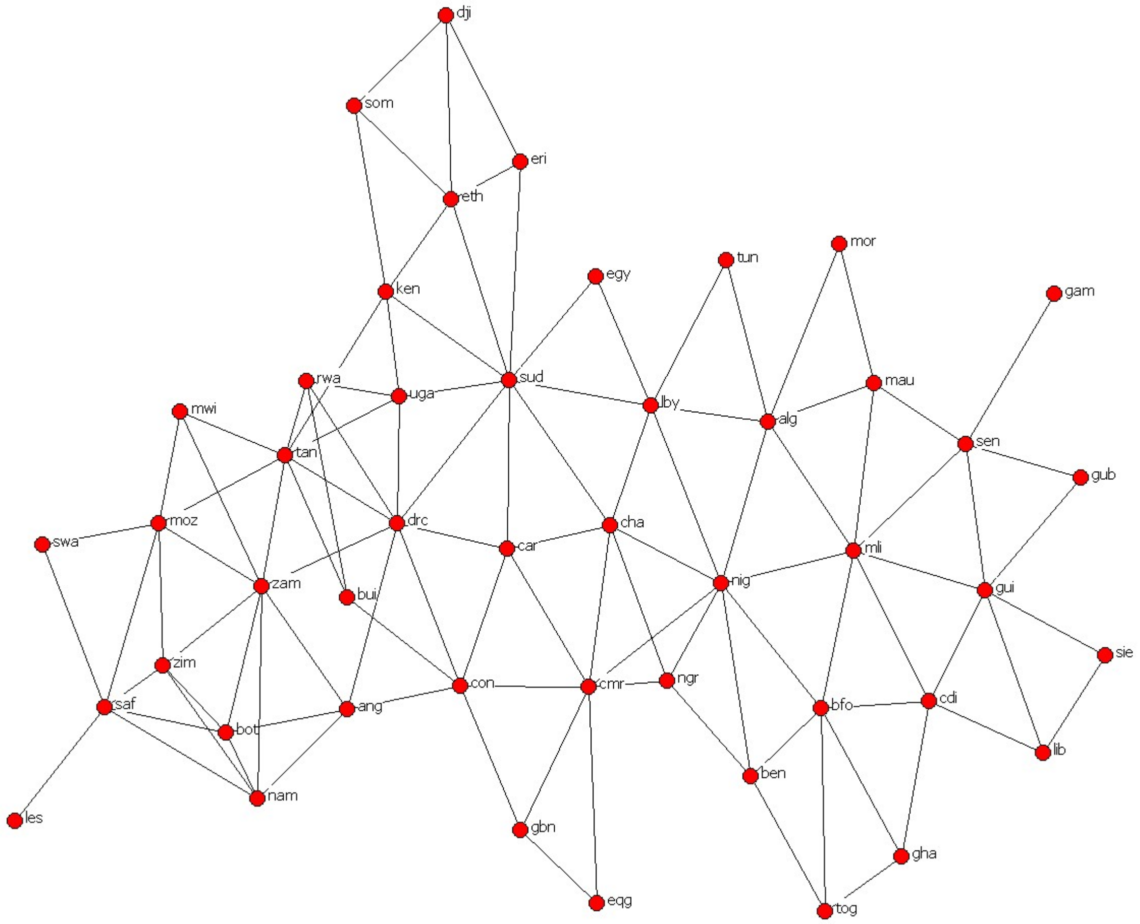
[4] Available at: www.prio.no/cwp/armedconflict. See Gleditsch (2007) for further details on the sources and rationale behind his dataset.

[5] This differs from Gleditsch's (2007) focus on the year of war onset. However, a network analysis of onset data requires individual network maps for each year, which are not yet available.

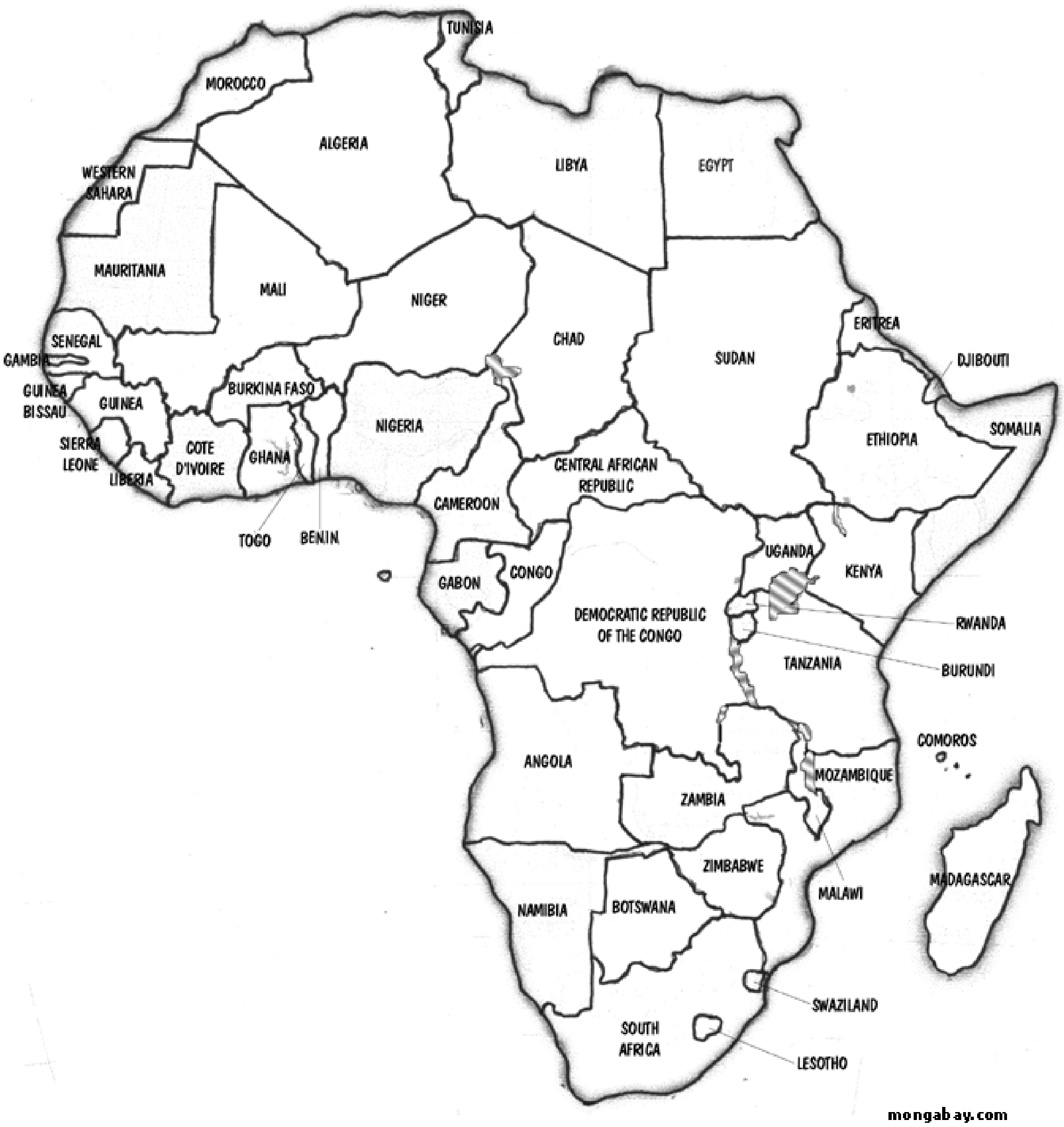
Figure 1. Network of countries on the African continent (with list of abbreviations).



Abbreviations:

alg	Algeria
ang	Angola
ben	Benin
bfo	Burkina Faso
bot	Botswana
bui	Burundi
car	Central African Republic
cdi	Cote d'Ivoire
cha	Chad
cmr	Cameroon
con	Republic of the Congo
dji	Djibouti
drc	Democratic Republic of Congo
egy	Egypt
eqg	Equatorial Guinea
eri	Eritrea
eth	Ethiopia
gam	Gambia
gbn	Gabon
gha	Ghana
gub	Guinea Bissau
gui	Guinea
ken	Kenya
lby	Libya
les	Lesotho
lib	Liberia
mau	Mauritania
mli	Mali
mor	Morocco
moz	Mozambique
mwi	Malawi
nam	Namibia
ngr	Nigeria
nig	Niger
rwa	Rwanda
saf	South Africa
sen	Senegal
sie	Sierra Leone
som	Somalia
sud	Sudan
swa	Swaziland
tan	Tanzania
tog	Togo
tun	Tunisia
uga	Uganda
zam	Zambia
zim	Zimbabwe

Figure 2. Political map of countries on the African continent.



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There are a vast number of variables that can be extracted to describe a network (Barabási 2003; Jordán, Benedek, and Podani 2007; Jordán, Liu, and Davis 2006; Jordán et al. 2006). These variables can comprise information about the absolute or relative position of nodes, links and 1st and 2nd order (and so on) neighbors. Each variable measures different properties of the network structure, and a node's position in it. In this paper, we focus on two basic measures of a state's "network centrality" or "positional importance" relative to other nodes in the network: node degree and topological importance.

Node degree (D)—The simplest approach takes node "degree" (D) as a measure of centrality. D_i simply represents the total number of direct neighbors of a given node *i* (see Figure 3). The rank order of D values within a given network provides a very basic quantification of the structural (topological) importance of nodes in the network, i.e. how many other nodes they are linked to. A higher D corresponds to a greater connectivity to other parts of the network.

Topological Importance (TI^1 and TI^2)—An alternative index takes into account the number of *neighbors of neighbors.* Rather than just adding them up, however, a measure of "topological importance" (TI) can be calculated which represents a given node's relative influence in a given neighborhood of the network (see Figure 3). In other words, TI offers a measure of *indirect* topological importance (as opposed to *direct* topological influence given by D), given *its* neighbors' *own* neighbors. The influence goes in both directions: from a given node to its neighbors, and from those neighbors to the given node.

TI can be calculated for any iteration of neighbors of neighbors, from 1,2,3…*n*-steps, denoted TI^n. We define $a_{n,ij}$ as the effect of node *j* on node *i* when *i* can be reached from *j* in *n* steps (in this paper we will stick to just 1 and 2-step effects). The simplest mode of calculating $a_{n,ij}$ is if $n = 1$ (i.e. the effect of *j* on *i* in 1 step): $a_{1,ij} = 1/D_i$, where D_i is the degree of node *i*. At the maximum number of steps, the effect received by node *i* from all nodes in the same network is equal to 1. The topological importance of the *n*th-step, σ, originated from state *i* is defined by the following formula:

$$\sigma_{n,i} = \sum_{j=1}^{N} a_{n,ji} \qquad (1)$$

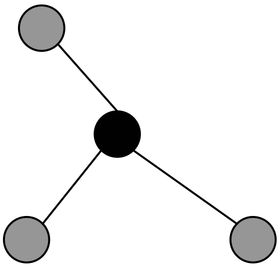
where *N* is the total number of nodes in the network. Effects originated from different nodes are typically different. Here, we define the topological importance of node *i* when effects "up to" *n* steps are considered as follows:

$$TI_i^n = \frac{\sum_{m=1}^{n} \sigma_{m,i}}{n} = \frac{\sum_{m=1}^{n} \sum_{j=1}^{N} a_{m,ji}}{n} \qquad (2)$$

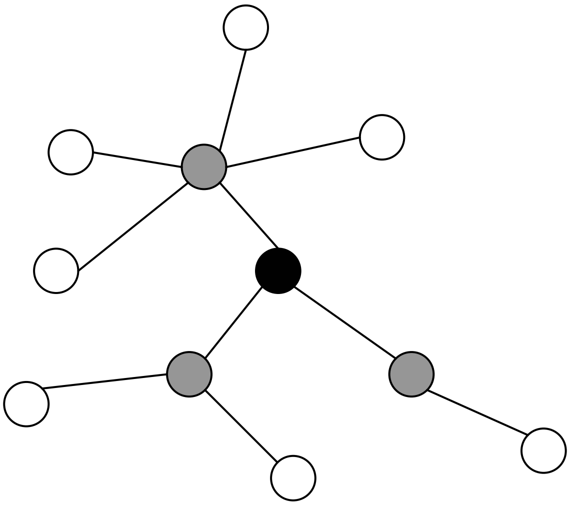
which is simply the sum of effects originated from node *i* up to *n* steps (1 + 2 + 3…up to *n*) averaged over the maximum number of steps considered (i.e. *n*).

Figure 3. A given node's network centrality as measured by its number of neighbors (D), its topological importance compared to immediate neighbors (TI^1), and its topological importance compared to second-neighbors (TI^2).

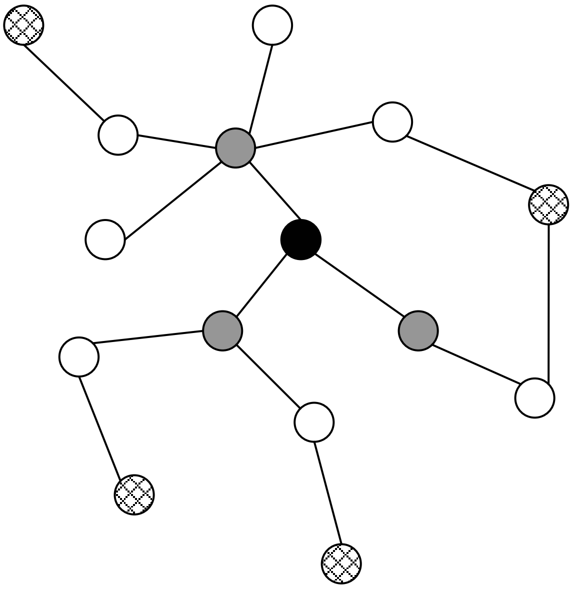
D



TI^{1}



TI^{2}

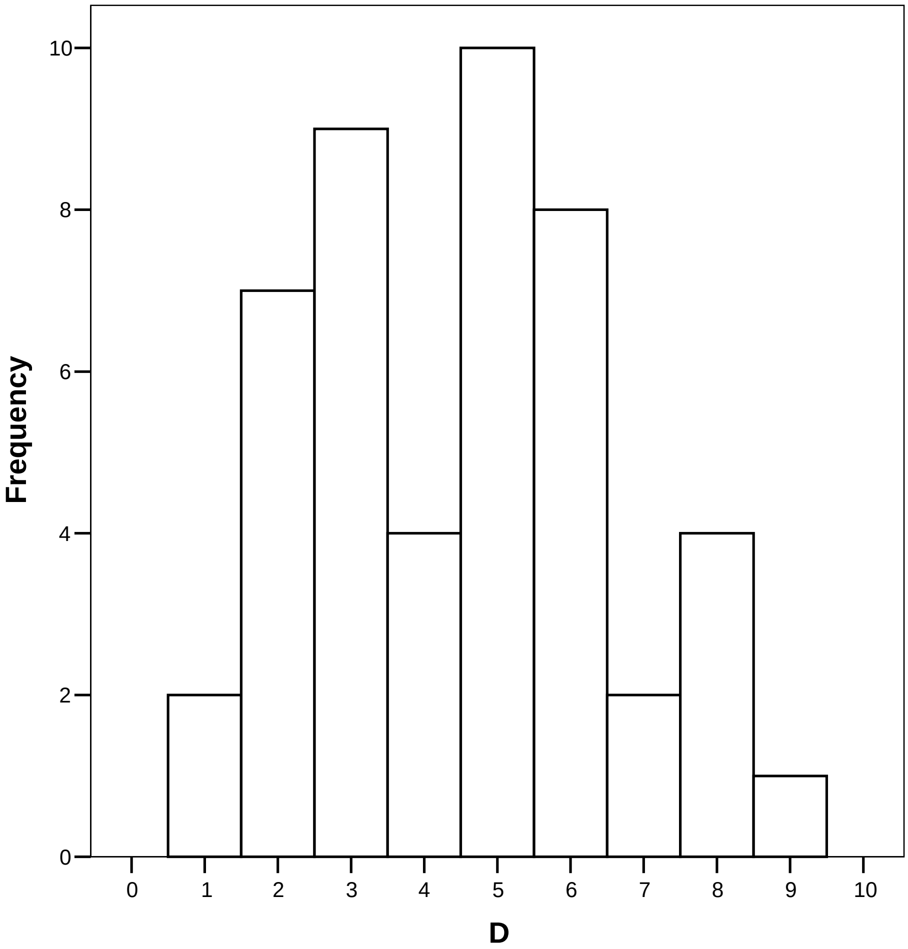


RESULTS

Characterization of the Network of African Countries

One way to characterize the overall network structure is to look at the distribution of first-order links (D). The mean number of links is 4.51 (median 5, mode 5, standard deviation 2.04), and ranges from 1 (Gambia, Lesotho) to 9 (Sudan). Figure 4 shows that the number of links follows an approximately normal distribution (Kolmogorov-Smirnov test: Z = 1.05, N = 47, p = 0.22). One notable feature (discernable from both Figure 4 and 1) that the network is fairly homogenous—that is, most countries tend to have a similar number of links. This suggests that states in different network positions are unlikely to have extremely large or small topological influence.

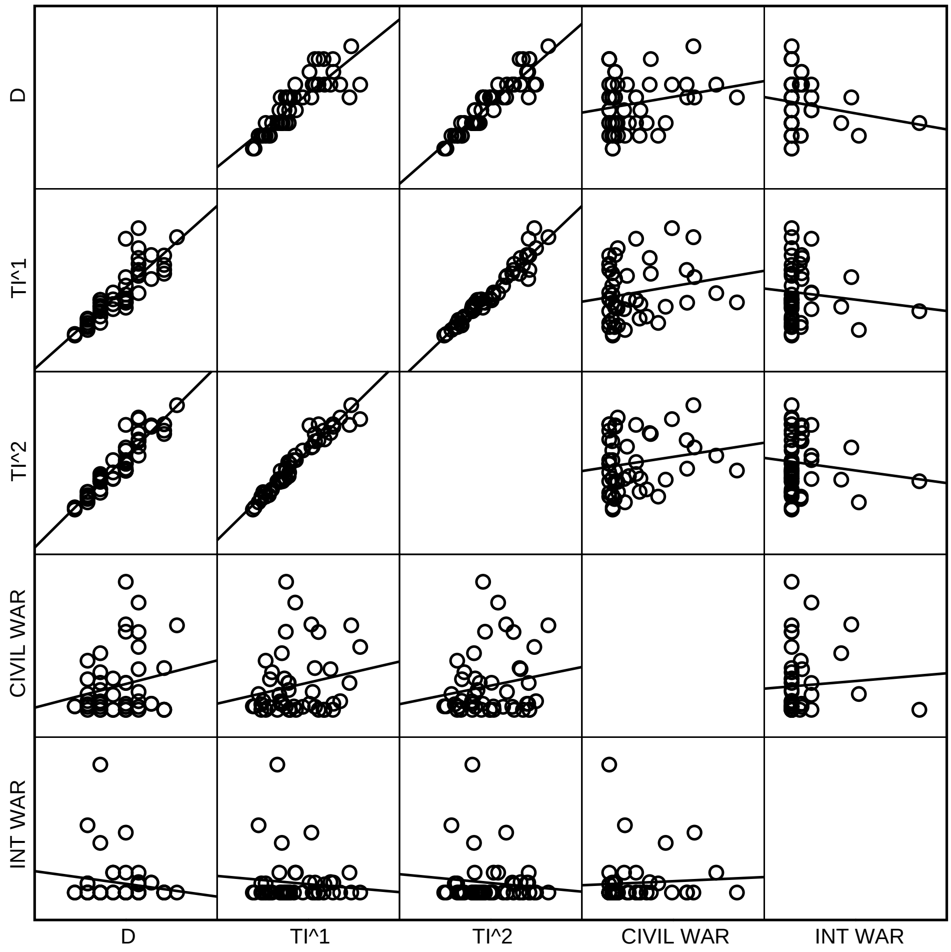
Figure 4. Distribution of links to neighbors (D) for countries on the African continent.



Network Centrality and War

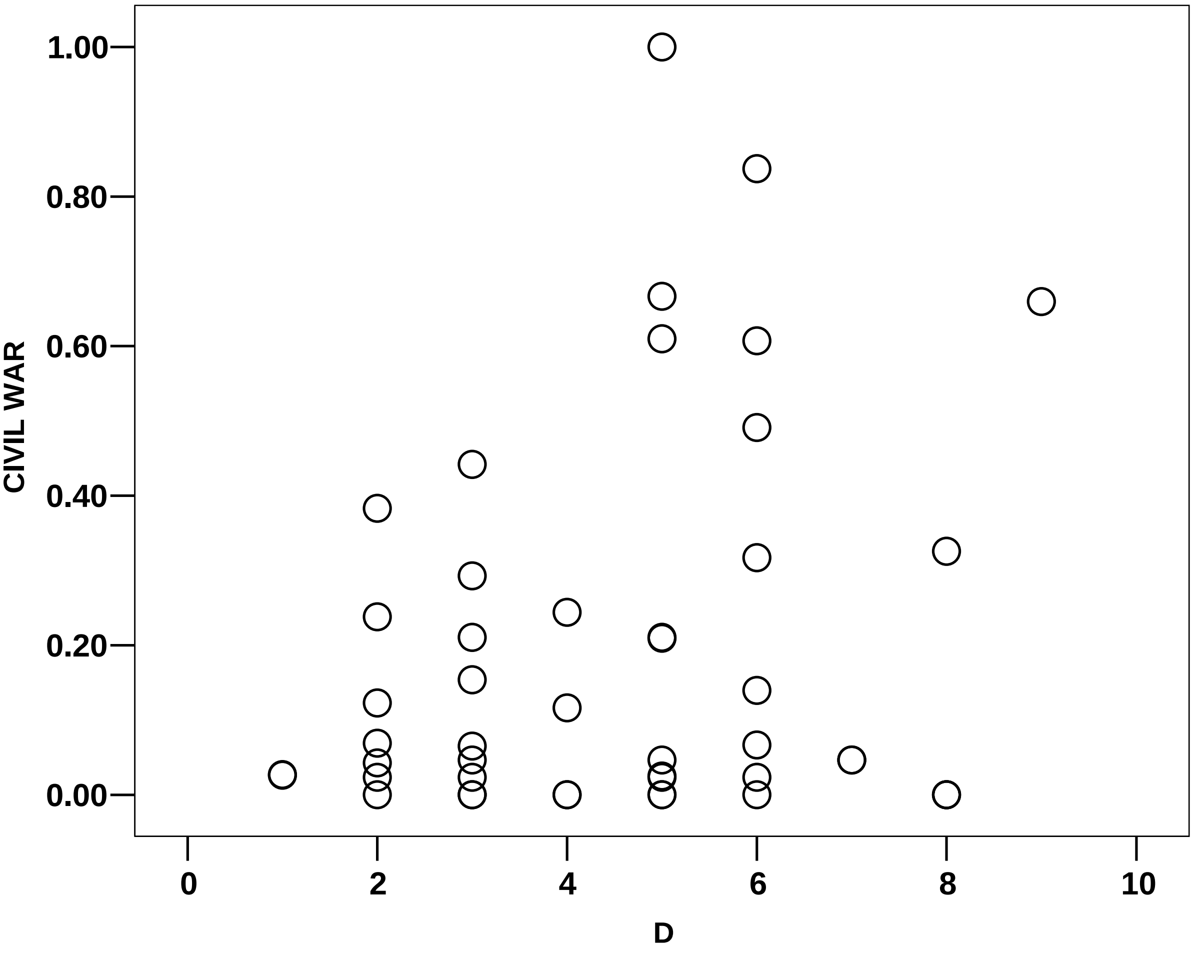
Figure 5 explores matrix correlations between network variables and war (civil wars and interstate wars). The general pattern is that each measure of topological importance, D, TI^1, and TI^2, is *positively* correlated with civil war (implying that states more imbedded in the network are more likely to experience civil war), but *negatively* correlated with inter-state war (implying that states less imbedded in the network are *more* likely to fight other states). Note that D, TI^1, and TI^2 are also tightly correlated with each other.

Figure 5. Matrix correlations between network indices and war.



For civil war, our a-priori prediction was that increased network connectivity increases civil war, so we can use a one-tailed test of the (Pearson) correlation coefficients, which reaches marginal significance for D ($r = 0.21$, $p = 0.077$; Figure 6), but less so for TI^1 ($r = 0.20$, $p = 0.091$) and TI^2 ($r = 0.18$, $p = 0.12$; $n = 47$ in all cases). There is some evidence, therefore, that both direct and indirect effects of one's network neighborhood influence the incidence of civil war. For interstate war, we did not have an a-priori prediction so we use a two-tailed test. The trend was systematically negative for each variable but did not approach significance (all $r > -0.16$, all $p > 0.29$). Logging either dependent variable (civil war or inter-state war) did not improve the fit for D, TI^1 or TI^2.

Figure 6. Civil wars are more common among states with more neighbors.



We also found a positive (non-significant) trend suggesting that more embedded states experience fewer but protracted civil wars rather that many short ones (two-tailed Pearson correlations for: D, $r = 0.23$, $p = 0.12$; TI^1, $r = 0.23$, $p = 0.11$; and TI^2, $r = 0.21$, $p = 0.15$; $n = 47$ in all cases). The dependent variable was the proportion of civil war years (as before) divided by the proportion of civil war *outbreaks*. Thus, a larger number represents fewer and/or longer wars, a smaller number represents many and/or short wars.

Multivariate Analyses

As noted above (Figure 5), D, TI^1 and TI^2 are intercorrelated with each other, so unsurprisingly they do not, in *combination*, much improve the explanation of variance in civil war (multiple regression with civil war as the dependent variable and D, TI^1 and TI^2 as independent variables: $F_{3,43} = 1.62$, $p = 0.20$; partial correlation coefficients for D, TI^1 and TI^2 are only of marginal significance, with p values between 0.10 and 0.12).

Although the above suggests some evidence for topological influences on civil wars, there are two remaining problems: (1) The relationships described above are weak and there is considerable scatter. This is unsurprising, however, given that civil wars have previously been shown have important causes in various country-specific factors that were absent from the statistics above (Fearon and Laitin 2003; Ross 2006; Toft 2003; Walter and Snyder 1999). (2) Civil wars may be related to network position not because of conflict contagion *per se* (in which conflict genuinely spreads from one country to another), but because of the clustering of conflict risk factors (i.e. conflict *appears* to "spread", but in fact conflict is just spatially auto-correlated because neighboring countries tend to share the same risk factors for war).

For both of these reasons, we need to control for country-specific variables and test whether network centrality plays a role over and above these other factors. Therefore, we conducted a multivariate analysis to test for a relationship between civil war and network position, while controlling for established predictors of civil war: democracy, ethnic dispersion, population, and GDP (the same control variables used by Gleditsch 2007).[6]

With civil war as the dependent variable, a multiple regression including all network *and* country-specific variables is actually a very poor fit ($F_{7,39} = 1.09$, $p = 0.39$; $R^2 = 0.16$). Partial correlation coefficients are again only of marginal significance for D ($t = 1.51$, $p = 0.14$), TI^1 ($t = 1.74$, $p = 0.09$) and TI^2 ($t = -1.74$, $p = 0.089$). For democracy, ethnic dispersion, population, and GDP, all $t < 0.88$, all $p > 0.38$. Results were very similar when using alternative dependent variables (*log* proportion of civil war years; proportion of years of civil war *outbreaks*; *absolute* number of civil war years), and a model *excluding* all three network variables was worse. Although the model fails to explain any significant variation in civil war, there are nevertheless four suggestive results that call for further analysis:

1. Risk factors for civil war often cited in the literature—democracy, ethnic dispersion, population, and GDP—failed to explain any variation in our

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[6] An alternative approach would be to trace the fine-scale movement of war events among states, although in this case statistical power would be weaker (we are examining methods of doing this).

measure of civil war in Africa (none approached significance). This casts doubt as to the validity of those risk factors for explaining civil wars in Africa.

2. Measures of network centrality contributed most to the (admittedly poor) model than any other independent variable (standardized coefficients were much larger, and approached significance), implying that topological importance may be at least as, or more important than, conventional causes of civil war.
3. The coefficients of TI^1 and TI^2 were larger than the coefficient of D, implying that—once other causes of war are controlled for—the *indirect* effects of network structure may be as or more important than *direct* ones (as with disturbed food webs).
4. The coefficients of D and TI^1 were *positive*, but the coefficient of TI^2 was *negative*, implying that the influence of neighbors on civil war may be good or bad at different hierarchical levels of the network (as with the rabbit-lynx paradox).

Modification of Dependent Variable

The dependent variable violates some assumptions of the linear models used above because it does not conform well to a normal distribution. The problem arises from "zero-inflation," as there are several (11) countries that experienced no war at all (and for which civil war = 0). This problem is tricky to solve because no transformation can normalize the data effectively. One solution is to simply exclude these cases, in which case the distribution is effectively normalized (Kolmogorov-Smirnov test: Z = 1.17, N = 36, p = 0.13). With this normalized data, there is a significant positive correlation between civil war and D (r = 0.36, p = 0.016; Pearson correlation, n = 36, one-tailed), and a marginally significant one with TI^1 (r = 0.26, p = 0.064), and TI^2 (r = 0.26, p = 0.063).

A multiple regression with civil war as the dependent variable and all three network indices as independent variables produces a significant model ($F_{3,32} = 3.60$, p = 0.024) explaining 25% of the variation in civil war. Partial correlation coefficients are significant for D (t = 2.81, p = 0.008), marginal for TI^1 (t = 1.91, p = 0.065), and significant for TI^2 (t = -2.24, p = 0.032).

Finally, repeating the multiple regression in the previous section with (normalized) civil war as the dependent variable and all network and country-specific variables now produces a much better fit ($F_{7,28} = 2.20$, p = 0.066), explaining 35% of the variation in civil war (although note that there are now a lot of independent variables for the reduced sample size). Partial correlation coefficients are of marginal significance for D (t = 1.95, p = 0.061), and not significant for TI^1 (t = 0.98, p = 0.34) or TI^2 (t = -1.43, p = 0.16). For democracy, ethnic dispersion, population, and GDP, all t < 1.6, all p > 0.13 and, as before, standardized coefficients for all network variables were larger than for any country-specific variable.

Overall, whether the dependent variable is left alone or truncated to achieve normality, the results are suggestive that network centrality may be an important influence on civil war, and further analyses would be worthwhile.

CONCLUSIONS

Civil wars do not appear to be randomly distributed across the network of African states. Instead, we find evidence that civil war is positively related, at a marginally significant level, to specific measures of a state's network centrality. Interestingly, measures of network centrality are *positively* correlated with civil war, but *negatively* correlated with inter-state war (implying that states more imbedded in the network are *more* likely to experience civil war, but *less* likely to fight other states). We also found that more embedded states tended to experience a smaller number of protracted civil wars rather that many short ones. Finally, a (poor fitting) multivariate model offers hints that, (a) measures of topological importance remain important when previously identified correlates of civil war are controlled for, and (b) there may be some indirect and counter-intuitive effects of civil wars which rebound through the network of connected states.

Together, these findings support the general idea that the behavior of states is influenced by their political "field" (and this may lead to both opportunities and constraints). Such findings are particularly interesting in the light of research in the life sciences, in which network centrality and indirect effects can prove to have significant influences on the survival or wellbeing of individuals in the network, and on the stability of the network as a whole. Simulation studies in ecology, for example, suggest that a species' probability of extinction correlates with its number of neighbors in food web graphs (Jordán, Scheuringy, and Vida 2002). Although extinction is a rare event among modern states, the wellbeing of its economy, political system, and inhabitants is clearly affected by regional geopolitics. We find, in support of this, that the number of neighbors among African countries is positively, but non-significantly, correlated with their level of vulnerability according to the 2007 Failed States Index ($r = 0.20$, $p = 0.18$; data source: fundforpeace.org).

Network analysis offers a burgeoning toolkit for generating novel data and testing novel (and old) hypotheses in international relations. Improvements we hope to make in the future include: weighting links by the lengths of country borders (longer borders imply greater influence); integration with GIS data on geographic variables such as types of terrain between countries; the calculation of country-specific variables for immediate and distant clusters of neighbors (e.g. does the summed level of civil wars among neighbors correlate with the level of civil war at home?); and widening the analyses to examine other continents with more heterogeneous topologies (landmasses with bottlenecks, for example, are likely to reveal very different country-level influences depending on network location).

To conclude, using a different approach and a different dependent variable, our analysis lends support to Gleditsch's (2007) basic finding that there are important transnational dimensions to civil war. Indeed, our results identify a transnational dimension to civil wars based *purely on network topology*—excluding any information at all on country-level factors. Topological position thus appears to be a potentially important correlate of civil wars in Africa, and further research is needed to understand exactly when and why this occurs.

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