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The effects of shocks on international networks: Changes in the attributes of states and the structure of international alliance networks

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Abstract

We study the effects of shocks – such as major wars that change states' strategic environments – on alliance networks. This has important implications for the structure of security cooperation networks. We develop an agent-based model (ABM) that: (1) models network evolution processes of security cooperation networks; (2) induces shocks that cause significant changes in agents' utilities due to shifts in common interests between states; (3) analyzes how networks reorganize in the post-shock period. We derive propositions from the ABM about the relationship between shock attributes and network structure. We compare the results of the ABM to similar shocks that operate on real-world alliance networks. The ABM results with random network data suggest that states that experience dramatic changes in their strategic environment increase network connectivity and consistency. Consequently, post-shock networks become increasingly connected (denser) and consistent (transitive). With a few notable exceptions, these results are corroborated by analysis of alliance network reorganization following shocks. We discuss the theoretical and empirical implications of the results and offer directions for future research on shocks and international networks.

Keywords

agent-based models, alliance networks, homophily, network connectivity, network consistency, network reorganization, shocks

> 'We [England] have no eternal allies and we have no perpetual enemies. Our interests are eternal and perpetual, and those interests it is our duty to follow.'
>
> Lord Palmerston, remarks in the House of Commons, 1 March 1848.

Introduction

Major international conflicts can cause leadership turnover (Bueno de Mesquita, Siverson, & Woller, 1992; Chiozza & Goemans, 2004), drastic changes in economic growth (Organski & Kugler, 1980), territorial change, and population shifts (Diehl & Goertz, 2000). Some conflicts have structural effects on the international system (Brecher, 2008; Gilpin, 1981). International conflicts alter the challenges to states' security and the structure of their interests. Yet, we have limited knowledge on how such shocks affect behavior, and the implications for the structure of international networks.

To motivate this study we show in Figure 1 how shocks have influenced alliance neworks over time. Some shocks (e.g. World War II) have a brief, spike-like effect on the density of alliance networks, with density quickly returning to a stationary equilibrium. However, shocks

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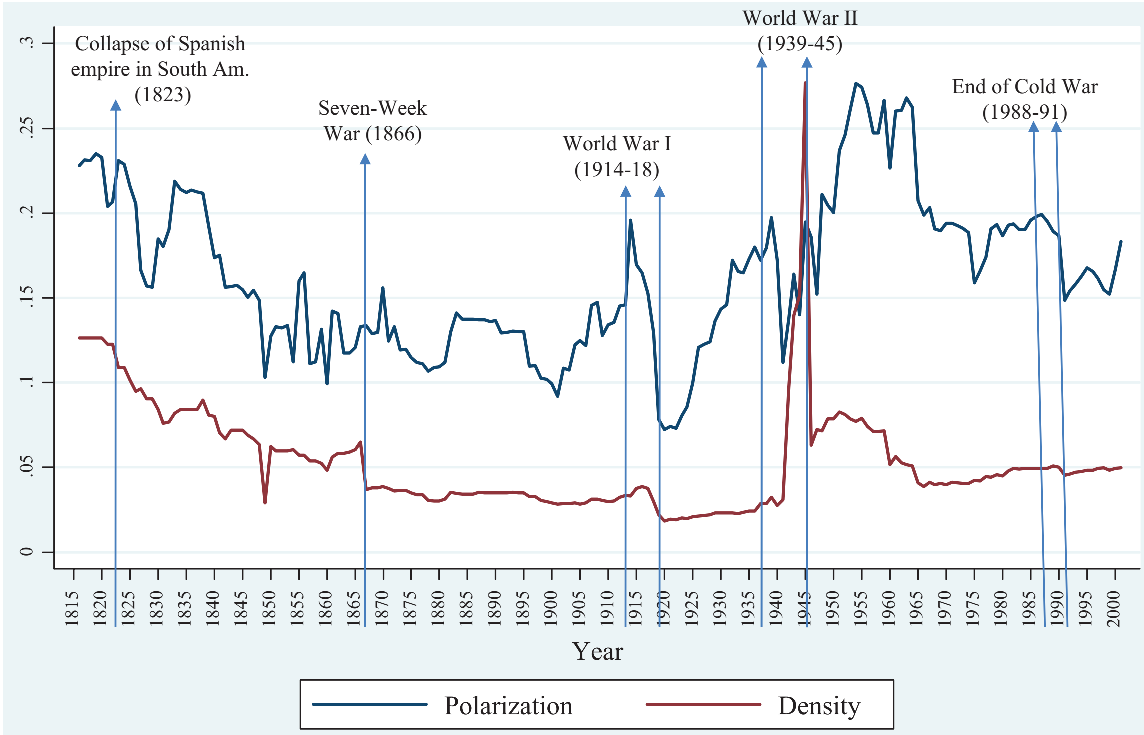

Figure 1. The polarization and density of international alliance networks, 1816–2004
Sources: Leeds, 2005; Maoz, 2010.

had a lasting effect on alliance polarization (i.e. the degree to which the network approaches strict bipolarity), producing a new trend or equilibrium.

Consider two critical turning points in international history: the end of World War II, and the end of the Cold War. During WWII, the USA and Great Britain formed an alliance with the Soviet Union against Germany. Once the war ended and tensions between the former allies increased, the Western states formed NATO and the Soviets formed the Warsaw Pact. Former enemies – the United States and Japan and France and Germany – became allies, and former allies – the United States and China – became adversaries. The collapse of the Warsaw Pact at the end of the Cold War was followed by the expansion of NATO, with some Eastern European states joining their former adversarial alliance. Here too, former adversaries became allies, and former allies (i.e. the new Eastern European NATO members and Russia) became potential adversaries.

Our study centers on the way shocks – events that cause dramatic change in states' interests – affect the structure of alliance networks. Specifically, we study how these shocks – changes in the identity of shared enemies – affect the propensity of states to form or break alliances, and the network implications of such decisions. The following questions guide the present study:

(1) How do shocks affect alliance network reorganization?
(2) What is the relationship between the characteristics of a shock (e.g. size, spread, magnitude) and the structure of post-shock network reorganization?

We employ a two-step strategy. First, we develop an agent-based model (ABM) that simulates network formation and network evolution processes. The ABM enables us to deduce hypotheses on how shocks affect international networks. Second, we test these hypotheses by comparing the ABM results to the effects of shocks on real-world security cooperation networks.

Most studies of shocks in networks focus on network resilience. By contrast, the innovation of our study is in showing how shock characteristics (e.g. size, spread, magnitude) affect network reorganization. This is done by comparing the pre-shock structure of networks to their post-shock structure, and by comparing the results of an ABM with random network data to real-world international networks. In the next section we offer a brief review of the literature on the effects of shocks on physical, social, and political networks.

Shocks and international networks

A network is composed of nodes (individuals, organizations, states) and a rule that defines the presence or absence, direction, magnitude, and/or sign of a link between any two nodes (Maoz, 2010). We focus on discretionary networks in which links are the result of nodal choices. Discretionary international networks include alliances, trade, IGO membership, arms transfers, militarized disputes, etc.). Network analysis is a science of interactions containing ideas, measures, methods, and models that analyze the formation, evolution, and structure of physical, economic, or social interactions. The study of shocks within or across systems is a key aspect of network science, with important theoretical and practical implications.

The idea that shocks influence various aspects of international politics is not new. Shocks affect the structure of the international system (Gilpin, 1981; Brecher, 2008) and the outbreak and termination of international rivalries (Goertz & Diehl, 1995; Diehl & Goertz, 2000). The fall of empires (the Austro-Hungarian and Ottoman empires in 1918, the British and French empires in the 1950s and 1960s, and the Soviet Empire in the late 1980s) had a dramatic effect on the international system, resulting in state formations, regime changes, and global realignments. Revolutions have significant effects on international conflicts (Maoz, 1989, 1996; Walt, 1992; Colgan, 2013).

Studies of the effects of economic shocks on political stability yield mixed results. Bazzi & Blattman (2014) find that price shocks do not significantly impact civil and interstate conflict. Hull & Imai (2013) find that foreign interest rates shocks increase the likelihood of civil conflicts in small open economies. Nielsen et al. (2011) find that dramatic reductions in foreign aid increase the probability of internal conflict. However, these studies focus on individual states rather than on international networks.

A critical research area concerns the effects of environmental shocks on conflict (e.g. Nel & Righarts, 2008; Salehyan & Hendrix, 2014; Klomp & Bulte, 2013). Yet, these studies also focus on individual states or other social units; they do not ask how social networks of relevant political actors affect the probability of a shock translating into protest, unrest, revolution, or full-scale civil war. This lack of attention to network dynamics further extends to the study of network reorganization, which is a key concern in determining the resilience of social systems.

While research on shocks suggests important results, it suffers from several problems. First, the causal mechanisms underlying shock-related effects are poorly understood. Second, it is unclear whether these effects are generalizable across different types of shocks (e.g. wars versus economic crises, empire collapse versus revolutions). Some research connects different characteristics of the international system to the probability of such shocks. These works suggests that polarization increases the probability and magnitude of war; political revolutions and regime changes tend to diffuse spatially (Maoz, 1996, 2010; Starr, 1991; Starr & Lindborg, 2003). Yet, these results are largely inductive and offer no insights into the dynamics of shock-related effects and network reorganization.

Models of cascades in networks bear little relevance for international relations as they focus primarily on nodal collapse. Yet, permanent state collapse is quite rare. What we do observe with some regularity, however, is that some states – due to internal or external circumstances – are forced to drop some or all of their ties with other states. This often happens due to drastic alterations in their attributes. Shocks such as leadership change, democratization, and a changed structure of the state's strategic environment affect the willingness and ability of the focal state to form ties. They also alter the attractiveness of the changed state as a partner for security or economic cooperation. Finally, there is little evidence on patterns of network reorganization following shocks. These are the principal lacunae that we aim to fill with the present study.

Preliminary ideas about shocks and international networks

Our ideas juxtapose known aspects of international networks and network evolution processes with notions about how states restructure their relations following shocks. For now, we focus only on exogenous shocks. This is a simplifying assumption, as most of the shocks in international networks are endogenous. We plan to relax this assumption once we have a better grasp of the processes that may cause a network or some of its elements to fail following an exogenous shock. Our investigation is guided by several assumptions:

(1) *Networks are emergent structures*. Many international networks form and evolve as a result of states' choices to form links with one another.

These decisions have both intended and unintended consequences. Thus, understanding network evolution and post-shock reorganization requires a model of when, how, and why states choose partners. Once we understand this process, we can connect individual and dyadic choices to the resulting structural characteristics of networks.

(2) *All nodes use the same set of rules to decide whether and with whom to form ties of various types*. We rely on this assumption because it simplifies our model.

(3) *Partner selection is based on utility maximization principles*. States enter security cooperation reluctantly (Mearsheimer, 2001; Maoz, 2010). They do so when they cannot meet security challenges via their own resources. Thus, when states' consider would-be allies, they opt to find those allies that offer them the most reliable and effective support, and, at the same time, minimize the likelihood of unwanted conflict.

(4) *Shocks do not alter the calculus of tie-formation or the logic of choosing partners*. Shocks do not alter the fundamental logic of security cooperation. Rather, shocks change the attributes of states, thus making some of them more attractive and others less attractive alliance partners. Understanding how shocks affect networks requires an explanation of how states adapt to those changes, given the micro-foundational logic of network evolution.

Before reviewing the network evolution process, we discuss the type of shocks that are the focus of the present study. Much of the literature on international cooperation and conflict claims that states' interests drive behavior. This is well reflected in Palmerston's argument. Shared interests are consequently seen to have a strong effect on international cooperation. Realist scholars claim that states have common interests to the extent they have common enemies (Mearsheimer, 1994/95; Gowa, 1999; Maoz, 2010). Thus, changes in the identity of shared enemies affects change in states' interests resulting, possibly, in changes of alliance ties.

A significant consequence of wars – particularly major and multilateral wars – is that they cause dramatic shifts in patterns of relations. As we have seen in the examples discussed in the introduction, former friends may become enemies, and former enemies may become allies. In this context, states experience two types of shocks. The first is a *positive shock*, wherein two states that did not share enemies in the past now share at least one common enemy. This may happen as a result of a conflict between a state's enemy and another state. The German attack on the Soviet Union in 1941 formed a common interest between the Soviet Union and Britain. The Japanese attack on China in 1936 and on the USA in 1941 formed a common interest between China and the USA. A positive shock increases the convergence of interests between two states and should increase the probability of alignment.

Second, a *negative shock* occurs when two states that shared a common enemy in the past no longer share one, which may result from peace treaties or a termination of a conflict between a state's enemy and one of its own enemies. The end of WWII converted the common interests between Britain and the Soviet Union and between the USA and China – due to shared enemies – to long-term rivalries. Negative shocks increase interest divergence, and should reduce the incentive to ally or increase the incentive to sever alliance ties. Note that states may experience positive shocks and negative shocks simultaneously as some of their rivalries end and others begin. The magnitude of these shocks is a function of the sizes of each shock type and the number of states experiencing them.

Figure 2 shows the distribution of positive and negative shock magnitudes over time using the dyadic MID data (Maoz, 2005). We discuss these measures below. At this juncture, note the correlation between the level of conflict in the international system (the proportion of MID dyads) and the magnitude of these shocks. This correlation between conflict and shocks that change states' strategic environments drives our story of network reorganization.[1]

Our story combines processes of network formation and network evolution prior to shocks and processes of post-shock network reorganization. First, states define their need to form security cooperation ties. A state that lacks resources to deal with the security challenges it faces may be inclined to seek allies. In such cases, the state needs to determine how many allies it requires. This is the state's tie-capacity. Tie-capacity reflects the need for allies and the state's willingness and ability to commit to helping them (Maoz, 2010: 150–151; Snyder, 1997). The actual number of a state's security ties (its degree centrality) may equal its tie-capacity or be less than its

[1] The correlation between the proportion of MID dyads and positive shock magnitude is 0.76 and the correlation between MID dyads and negative shock magnitude is –0.38.

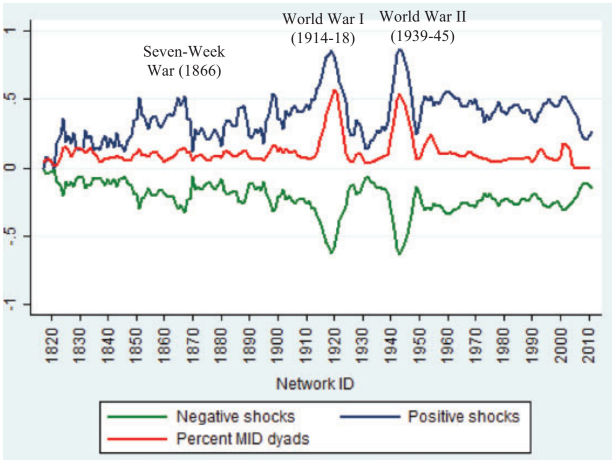

Figure 2. Proportion of states that experienced positive and negative shocks, 1816–2010

Positive shock magnitude $= \frac{1}{n}\sum_i (\textit{positive shock size})_i$.

Negative shock magnitude $= \frac{1}{n}\sum_i (\textit{negative shock size})_i$.

Percent MID dyads = proportion of dyads involved in MIDs.

tie-capacity if not all other would-be allies accept the state's offers.

Second, states rank would-be allies in terms of their attractiveness, or utility. Once a state has identified a potential partner, it offers to form an alliance. Such an alliance is formed only if the target accepts the offer.[2] If an offer is rejected, the state turns to other potential partners. This offer-making process iterates until the focal state reaches its tie-capacity, or no more offers are accepted.

In the current study we focus on a well-known type of network formation process: the homophily model (McPherson, Smith-Lovin & Cook, 2001; Newman, 2003). This model was shown to provide a good fit to alliance networks (Maoz, 2012). Homophily is predicated on the notion that partner selection depends on two sets of factors: common interests and similarity of nodal attributes. Previous research suggests two major attributes that serve as elements of the homophily function: joint democracy (Siverson & Emmons, 1991; Maoz, 2010) and cultural similarity (Maoz & Henderson, 2013; Maoz, 2012). A third component of attraction that affects alliance ties – common interests defined in terms of shared enemies (Mearsheimer, 1994/95; Maoz et al., 2007) – forms the center of our study. The fundamental differences between the alliance-making logic of democracies and autocracies suggests that, while both types of states use the same similarity and common interest factors to determine the desirability of would-be alliance partners, they assign different weights to these factors (Maoz, 2012).[3]

At any given point in time, states may rewire (i.e. switch allies), based on their updated evaluation of the structure of the current alliance network. States' utilities for partners changes as a function of the alliances formed by other states. Thus, some states may have an incentive to switch allies in order to maximize their utility. Rewiring entails dropping less valued allies in favor of more valued allies. The system may reach equilibrium if no more offers are made or none are accepted.

Dramatic changes in the identity of friends and foes force states to revise their utilities. The gain of new potential allies (new nodes with shared enemies), or a decline in the attractiveness of existing allies who no longer share enemies with the focal state, changes the focal state's utility. Major wars increase the likelihood of large-scale rewiring processes, even if the rules that govern the post-shock network reorganization process are the same as those that guided the pre-shock network evolution. This may lead to dramatic shifts in the structure of alliance networks. These shifts can be examined by comparing pre-shock networks to post-shock networks.

What are the expectations about the relationship between pre- and post-shock network characteristics? The causal mechanism focuses on the changes in utility functions due to shocks. As noted, shared interests – defined in terms of shared enemies – are a key element of the utility functions of states related to alliance formation. When shocks change the identity of states with shared enemies they cause changes in such utilities. The overall parameters of the network have not changed – we have the same nodes and the same rules that drive alliance choices. Nor do we examine changes in the attributes that make a state more or less attractive as an alliance partners – for example, its regime type or its culture. The key change we study here focuses on the common interest element of states' utilities. Specifically, a shock due to a major war may cause a dramatic shift in the strategic environment of states, resulting in dramatic shifts in their interests, which, in turn, renders some of them more attractive and other less attractive as alliance partners.

We discuss the general intuition of the expected effects of shock characteristics on alliance networks. The appendix provides a more detailed outline of these effects. Our focus is on two key parameters that define

[2] Alliance formation requires reciprocity. However, alliance termination can be unilateral.

[3] We also present evidence of this point in the Online appendix (Table A2).

network structure: *connectivity* and *consistency*. Connectivity measures the degree of attachment in a network across levels of analysis. At the nodal level, connectivity refers to the degree centrality of individual nodes (centrality). At the dyadic level, this refers to the probability of a dyadic edge. At the network level connectivity is network density – the proportion of realized ties to the number of possible ties.

Consistency measures the degree to which edges are internally consistent. A consistent relationship is one that can be logically inferred from other relationships; for example, 'the friend of my friend is my friend', or 'the enemy of my enemy is my friend'. At the nodal level, this refers to local transitivity – the ratio of closed triangles associated with a node to the number of possible triangles associated with this node. At the dyadic level, consistency is measured in terms of structural equivalence (Maoz et al., 2006) – the correlation between the relational profiles of dyad members. At the network level, consistency is measured by global transitivity or clustering coefficient (Watts, 2003), that is, the ratio of closed triads in the network to the number of possible closed triads. The effects of shocks on other network parameters are the focus of subsequent studies.

Shocks may have direct effects and indirect effects. *Direct effects* are due to changes in the strategic environment of the focal state. *Indirect (neighborhood) effects* are due to changes in the strategic environment of the focal state's allies (i.e. its network neighborhood). Shocks have a fairly intuitive direct effect on a state's network position: a rise in the number of states that share enemies with the focal state increases their relative utility as alliance partners. Therefore, *ceteris paribus*, the connectivity (centrality) and consistency (transitivity) of the focal states should increase. Negative shocks – a decline of the number of states with which the focal state shares enemies – should reduce the attractiveness of the latter and should have a negative impact on the focal state's centrality and transitivity.

A positive change in the shared-enemies indicator for dyad members raises the utility they assign to each other and increases the probability of dyadic edge. It also leads to a more consistent profile of alliance ties (structural equivalence). At the network level, a positive net increase in the number of dyads with shared enemies raises the total utility of the network (what Jackson & Wolinsky (1996) call *efficiency*), and should result in increased connectivity (density) and consistency (clustering coefficient). The opposite is expected given negative shocks.

Neighborhood effects highlight a key insight of network science: the dependency structure in a network has an important – sometimes counter-intuitive – impact on individuals, dyads, and the network as a whole. When a state's neighbors experience positive shocks (that is, they face a larger number of states with shared enemies than in the past), the relative utility they assign to the focal state declines. This suggests an expected drop in the focal state's connectivity. By contrast, neighbors experiencing negative shocks (loss of potential allies) may increase the relative utility they assign to the focal state. This results in an increase of the focal state's connectivity.

However, some of the focal state's neighbors experience positive shocks while others experience negative shocks. Thus the overall effects of neighborhood shocks on connectivity depend on the relative sizes of such shocks. Specifically, when the net magnitude of positive neighborhood shocks is positive (the number of neighbors that experienced positive shocks and the size of such shocks are larger than the number of neighbors experiencing negative shocks and the size of such shocks), we may observe a drop in nodal connectivity and transitivity. Conversely, when the net magnitude of neighborhood shocks is negative, nodal and dyadic connectivity should increase.[4]

Consequently, we deduce the following general hypotheses:

H1. Positive shocks: An increase in the number of nodes (states) that share enemies with the focal node (state) increases connectivity at the nodal (centrality) dyadic (edge probability) and network (density) level; positive shocks also increase consistency at the nodal (local transitivity) and dyadic (structural equivalence) level.

H2. Negative shocks: A decrease in the number of nodes that share enemies with the focal state decreases nodal and dyadic connectivity and consistency.

H3. Neighborhood shocks: The number of nodes in the focal state's neighborhood that experience shocks and the size of the shocks they experience tend to reduce nodal and dyadic connectivity and consistency. Negative neighborhood shocks tend to increase nodal and dyadic connectivity and consistency.

[4] Importantly, the concept of 'neighborhood effects' is different from what network analysts call 'network effects'. Network effects refer to the effect of endogenous network structure – defined in terms of such utility functions and characteristics as k-stars, closed triangles, edgewise shared partner, etc. – on nodal and dyadic choices (Warren, 2016; Haim, 2016). Our notion of neighborhood effects refers to the exogenous factors that operate on a node's neighbors – in this case, changes in their shared enemies' partners and the consequent effects on neighbors' utility functions.

H4. Shock magnitudes: The number of nodes that experience positive shocks, the sizes of the shocks, and the centrality of the shocked nodes have a positive impact on network connectedness (density) and consistency (clustering coefficient). Negative shock magnitudes reduce network connectedness and consistency.

Agent-based model of shocks and international networks[5]

We design an agent-based model (ABM) that captures the processes outlined above. ABMs are particularly suitable for this enterprise for several reasons.[6]

(1) *ABMs enable analysis of complex systems*. In our case, complexity is due to the number of agents, the number of ties, and the interaction of various types of shocks with different network formation processes. ABMs capture the process of self-organization within a controlled environment in terms of the initial conditions of the network and the characteristics of the shocks. Variation of either of these factors produces a very large number of combinations, which precludes purely analytic procedures. ABMs enable detection of general patterns of network dynamics, which may then be compared with empirical data.

(2) *ABMs allow for counterfactual analysis*. ABMs allow us to develop a better understanding of the features of a real-world process by comparing this process to alternate realities. The propositions generated from such comparisons can enrich the understanding of real-world international processes.

(3) *ABMs enable systematic process tracing*. Most empirical models estimate relationships within an input–output framework. They do not actually test the underlying causal mechanism. Even if a statistically significant relationship is found, it is not evident that the process that is expected to create this relationship is (a) unique, or (b) the best explanation of this relationship. ABMs actually capture the process specified in a given causal dynamic. A good fit between the ABM's patterns and real-world data provides evidence not only for the statistical significance of a relationship, but also for the validity of the process that produced it.

We discuss the general intuition of the ABM; a detailed description is in the Online appendix. The model evolves in four stages: *network formation*, *rewiring*, *shock*, and *network reorganization*. We examine networks of sizes from 20 to 200 nodes, which mimic the size of the interstate system over the period 1816–2010. Each node is randomly assigned a tie-capacity ranging from zero (isolates) to 70% of the network size. Nodes seek to maximize their overall utility, $U_i = \sum_j U_{ij}$ up to their tie-capacity via optimal selections of allies.

Network formation

We select 10% of the nodes in the network to randomly form ties with each other. The remaining nodes enter sequentially. Each node that enters the network may form ties with other nodes up to its tie-capacity.[7] Network formation is assumed to be homophilic. We use three attributes of homophily: democracy, common enemies (i.e. enemy of my enemy), and culture. We randomly assign these attributes probabilities that mirror the frequency of these attributes in real-world data. The probability of a node being democratic is 0.21, the probability of two nodes having common enemies is 0.32, and the probability of two nodes being culturally similar is 0.24.[8]

We employ a modified version of the Jackson-Wolinsky (1996) utility function that includes three components: (a) the direct worth of a node j to the focal node i, denoted by u^1_{ij}; (b) the indirect worth of node j based on the ties that j has with other nodes k in the network, denoted by u^2_{jk}; and (c) the cost of forming or maintaining a tie, denoted by c_{ij}. A general form of the utility function for a given pair of nodes ij is:

$$U_{ij} = u^1_{ij} + \sum_{(k \neq i | x_{jk}=1)} u^2_{jk} - c_{ij} \tag{1}$$

[5] The ABM is written in C#. The code for the ABM is provided in the project's website at http://maoz.ucdavis.edu/effects-of-shocks.html.

[6] For a discussion of ABMs and their advantages and disadvantages for political science research see Axelrod (1997), Cederman (1997), and Miller & Page (2007).

[7] These networks are undirected. A tie between nodes i and j is the same as a tie between nodes j and i.

[8] These numbers represent the mean values of the measures of joint democracy, shared enemies, and culturally similar dyads from 1816 to 2010. Data sources are given in Table II and the Online appendix.

The first-order utility between a pair of nodes is a function of the similarity of their attributes. We posit different tie-formation decisions based on regime type, as follows:

$$u^1_{ij} = \begin{cases} 0.5r_j + 0.3e_{ij} + 0.2s_{ij} & \text{if } r_i = 1 \\ 0.2r_j + 0.5e_{ij} + 0.3s_{ij} & \text{if } r_i = 0 \end{cases} \quad (2)$$

where $r_j = 1$ if node j is a democracy and 0 otherwise, $e_{ij} = 1$ if i and j have at least one common enemy (that is, a third party k that is an enemy of both), and 0 otherwise, and $s_{ij} = 1$ if the two nodes are culturally similar and 0 otherwise. This specification takes into account multiple traits and the idea that different types of nodes assign different weights to certain traits. The second-order utility u_{jk} is defined for the pair jk in the same way that u^1_{ij} is defined for the pair ij.

Note that the homophily function draws upon two insights from the alliance literature. First, the utility function combines common interests – defined as shared enemies and the focus of our analysis – and common attributes. Second, as noted above, we reason that democratic states and non-democratic states have different priorities in selecting alliance partners. We therefore assign different weights to the elements of the function according to the regime type of the focal state. The test of this function is in terms of how well it helps us predict alliance choices in the real world. We discuss this matter below.

The cost term is a function of the first-order utility assigned to the would-be ally and the number of available alternatives for alignment in the network; the higher the utility a node assigns to another node, and the fewer the alternative for ties, the higher the cost of the particular tie. Thus, the cost term is:

$$c_{ij} = \frac{u^1_{ij}}{n-1} \quad (3)$$

This specification reduces the utility function to:

$$U_{ij} = \frac{u^1_{ij}(n-2)}{n-1} + \sum_{(k \neq i | x_{jk}=1)} u^2_{jk} \quad (4)$$

The utility function takes into account the similarity between the would-be ally and its allies, but this similarity is discounted by the fact that it is of second order. A would-be ally is considered highly valued not only if it is similar to the focal node, but also if it is similar to other nodes in the network that are similar to the focal node. The focal node pays the price of an alliance directly to its would-be ally but not to the allies of the ally.[9]

Each node ranks all other nodes in terms of U_{ij} and offers to form a tie to the node with the highest utility. If that node is below its tie-capacity and the utility it assigns to the offering node (U_{ji}) is positive, the offer is accepted. If the offer is rejected (or if the offer is accepted and node i is still below its tie-capacity), i continues to the second-highest ranked node and repeats this process.[10] The node ends its tie-formation process when it has either (a) reached its tie-capacity, or (b) exhausted all existing nodes in the network. At this point, a new node enters and repeats the same the tie-formation process. This stage ends when the last node that entered the network completed its offer-making. Note that u^1_{ij} remains fixed as long as e_{ij} does not change during the pre-shock stage. However, the second order term u^2_{jk} changes as a function of rewiring.

Rewiring

Once the network reaches its size, nodes may rewire. A node is randomly selected. It recalculates its utility to all other nodes and rewires if: (a) it is below its tie-capacity and there is at least one other node j with $U_{ij} > 0$; or (b) it is at tie-capacity, but there exists at least one node j with whom the focal node does not currently have an alliance, and which provides it a strictly higher utility than its least-valued ally (i.e. $U_{(ij|x_{ij}=0)} > U_{(jk|x_{ik}=1)}$). In the second case, the focal node makes an offer to j. If j accepts (and this happens if either of the conditions stated above for i hold for j as well), then i rewires. If it was below its tie-capacity, then it adds the new alliance with j. If i was at its tie-capacity before rewiring, it replaces the ik alliance with the new ij alliance.

This process iterates with a new node selected for rewiring at each step. The rewiring stage ends in one of two conditions: (a) equilibrium, which is reached when no node wishes to rewire or no rewiring offer is accepted, or (b) if the rewiring process does not converge to equilibrium, we arbitrarily stop rewiring at

[9] Note that the second-order utility increases in the degree of the would-be ally. Hence if a would-be ally is connected to many other potential allies, its value as an ally increases, compared to a would-be ally that is highly similar to the focal state, but sparsely connected (or connected to many dissimilar states).

[10] If the node selected to make tie offers has multiple nodes with the same utility, we randomly select one node to receive the tie offer.

point 6N, so that each node has about 6 opportunities to rewire.

Shock
We simulate shocks by randomly changing the identity of enemies of enemies for a fraction of nodes that varies from 0 to 1. Some dyads with common enemies prior to the shock lose their common enemies, while others gain common enemies.

Post-shock rewiring
Once a shock is implemented, nodes begin to rewire. The rewiring process is similar to the pre-shock rewiring process. We choose a node at random and recalculate its utility with all other nodes, and repeat the rewiring process in the same manner as before the shock. The wider the spread of the shock (i.e. the more nodes that experienced either positive or negative shocks), the more widespread the process of restructuring that is expected to occur. This post-shock rewiring process ends in the same way as pre-shock rewiring: either the treatment network equilibrates, or we stop rewiring at 6N post-shock iterations.

Treatment and control networks
Prior to the implementation of shocks, we generate two networks: a control network and a treatment network. The *control* network simulates network evolution absent a shock, continuing the rewiring process without interruption. The *treatment* network is identical to the control network at 6N. However, at 7N it experiences a shock. From this point on, the treatment network rewires with the new enemy-of-enemy assignments. The rewiring process in both networks is identical. The same node is selected for rewiring in the control and treatment networks and uses the same rewiring rules as stated above. The only distinguishing feature is the presence of a shock, so that the rewiring node in the treatment network faces a new (larger or smaller) set of potential allies compared to the identical node in the control network. This allows us to compare parallel rewiring processes of shocked to non-shocked networks that are identical except for the shock parameters.

Measures of network characteristics

The ABM produces a wide range of network data at the nodal, dyadic, and network levels. We use these data to calculate network metrics for the pre- and post-shock networks at equilibrium. We review the network metrics and the shock characteristics in Table I. Most of the network metrics are well known, so we do not elaborate on them.[11]

Common controls
The bottom part of Table I provides information about a number of control variables that may confound shock effects on network reorganization. These control variables have been shown to affect alliance network structure in previous studies (e.g. Maoz, 2010, 2012; Cranmer, Desmarais & Menninga, 2012; Cranmer, Desmarais & Kirkland, 2012).

Network effects
For the monadic and dyadic network metrics, we control for network effects using a number of network statistics commonly used to estimate network effects including two- and three-stars and closed triangles. We also use an expected value estimate of network effects that is based on degree distributions. Since network-level analyses already reflect network effects, no such controls are needed at this level.

Measuring shocks in the real world

We use the alliance network derived from the ATOP project (Leeds, 2005) to examine the extent to which the patterns produced by the ABM match the real world. Empirical network metrics are identical to the metrics discussed above. However, the measurement of real-world shocks is more problematic. We provide a brief description of the measurement of shocks to the real-world networks; a more elaborate discussion is in the Online appendix.

To generate an enemy of enemy index, we use the dyadic MID dataset (Maoz, 2005). Briefly, for each year we generate an enmity network **E** in which entries $e_{ij} = 1$ if states i and j had a militarized interstate dispute (MID) during that year, and 0 otherwise. By squaring the **E** matrix we assign for each pair ij in $\mathbf{E}^2$ an entry of 1 if i and j share at least one enemy, and 0 otherwise.

Since the shock is specific to each dyad, we use the dyad-year as the basic observation. For each year we generate a difference matrix ($\hat{\boldsymbol{E}} = \boldsymbol{E}_t^2 - \boldsymbol{E}_{t-1}^2$). Positive entries in $\hat{\boldsymbol{E}}$ indicate a positive dyadic change: dyad $\hat{e}_{ij}$ gets a value of 1 if it did not have a common enemy at

[11] Wasserman & Faust (1997) is the most comprehensive source for most of these metrics. A more elaborate discussion of the network metrics is in the Online appendix.

Table I. Network metrics

Variable	*Measure*	*Time measured*	*Indicator of*	*Level measured*
ABM–Metrics of network formation				
Sequence of entry	$s_i = 0$ for first 10% of the network with random tie assignment $s_i = 1, 2, \ldots, n$ indicate sequence of entry into the network $S_i = \frac{s_i}{0.9N}$	Pre-shock Post-shock Control, treatment	Nodal 'age'	Nodal
Nodal acceptance rate	$AR_i = \frac{OA_i}{OM_i}$ where OA_i = no. of offers accepted for node i and OM_i = no. of offers made by node i.	Pre-shock Post-shock Control, treatment	Proportion of offers made by a node that were accepted by would-be partner	Nodal
ABM–Network metrics				
Nodal degree centrality	Degree centrality of nodes: $dc_i = \frac{\sum_j x_{ij}}{n-1}$	Pre-shock Post-shock Control, treatment	Nodal connectedness	Nodal
Local transitivity	Proportion of transitive triads associated with a node to the number of possible transitive triads given the nodal degree $lt_i = \frac{\sum_{j \neq i \neq k} x_{ij} x_{ik} x_{jk}}{\sum_{i \neq j \neq k} x_{ij} x_{ik}}$	Pre-shock Post-shock Control, treatment	Nodal consistency	Nodal
Edge	Assigned a value of 1 if an edge exists between nodes i and j; zero otherwise	Pre-shock Post-shock Control, treatment	Dyadic connectivity	Dyadic
Structural equivalence	Correlation between relational profiles of nodes i and j $seq_{ij} = r(ik, jk)$	Pre-shock Post-shock Control, treatment	Dyadic consistency	Dyadic
Density	Proportion of actual edges in the network to the number of possible edges $\nabla = \frac{\sum_i \sum_j x_{ij}}{n(n-1)}$	Pre-shock Post-shock Control, treatment	Network connectivity	Network
Transitivity	Proportion of closed triangles to the number of possible triangles in the network $T = \frac{6 \sum_i \sum_j \sum_k x_{ij} x_{ik} x_{jk}}{n(n-1)(n-2)}$	Pre-shock Post-shock Control, treatment	Clustering (network consistency)	Network
Average path length	Average length of path (number of edges) separating node i from other nodes in the network $L = \frac{1}{n-1} \sum_j \delta_{ij}$, where δ_{ij} is the shortest path separating nodes i and j	Pre-shock Post-shock Control, treatment	Inter-node distance	Network
ABM–Shock characteristics				
Positive shock size	New enemies of enemies added in the post-shock period as a proportion of total number of post-shock enemies of enemies $PS_i = \frac{\sum_j e_{(ij\mid s)} - \sum_j e_{(ij\mid 0)}}{\sum_j e_{(ij\mid s)}}$ if $\sum_j e_{(ij\mid s)} \geq \sum_j e_{(ij\mid 0)}$	Post-shock	Potential increase in direct utility nodes assign to each other	Nodal, dyadic, network

(continued)

Table I. (continued)

Variable	*Measure*	*Time measured*	*Indicator of*	*Level measured*
Negative shock size	Number of enemies of enemies dropped in the post-shock period as a proportion of number of pre-shock enemies of enemies. $NS_i = \frac{\sum_j e_{(ij\|0)} - \sum_j e_{(ij\|s)}}{\sum_j e_{(ij\|0)}}$ if $\sum_j e_{(ij\|s)} \leq \sum_j e_{(ij\|0)}$	Post-shock	Potential decrease in direct utility nodes assign to each other	Nodal, dyadic, network
Neighborhood shocks effects	Nodal: average shock sizes of a node's neighbors Dyadic: Maximum avg. shock size of nodal neighborhood effects	Post-shock		Nodal, dyadic
Shock spread	Proportion of nodes experiencing (positive or negative) a shock $PSS_i = \frac{1}{n}\sum_i \pi_i$, where $\pi_i = 1$ *if* $PS_i > 0$, $NSS_i = \frac{1}{n}\sum_i \tau_i$, where $\tau_i = 1$ *if* $\mathrm{NS}_i > 0$	Post-shock	Degree to which (positive/negative) shocks spread in network	Nodal, dyadic, network
Shock magnitude	Sum of shock sizes multiplied by degree centrality of nodes experiencing positive/negative shocks $PM = \sum_i PSS_i dc_i, NM = \sum_i NSS_i dc_i$		Positive/negative magnitude of shocks	Network
ABM–Control variables				
Pre-shock characteristics	In all analyses where a given post-shock network characteristic (e.g. nodal degree, dyadic structural equivalence, avg. degree in network) is regressed on shock attributes, we use the same pre-shock network characteristic as a control variable.			
Network size	Number of nodes	Pre-shock Post shock Control Treatment		Nodal, dyadic, network
Network effects	Two-stars, three-stars, closed triangles (explained in Online appendix)	Post-shock	Effects of endogenous network characteristics on nodal relations (or structural equivalence)	
U_{ij}	Utility of node *i* to alliance with node *j*	Pre-shock Post-shock	As defined in text (eq. [4])	Dyadic (averaged for nodal)
U_{ji}	Utility of node *j* to alliance with node *i*	Pre-shock Post-shock	As defined in text	Dyadic (averaged for nodal)

year *t*–1 but has at least one common enemy at year *t*. Similarly, dyad $\hat{e}_{ij}$ gets a negative dyadic change score if it had at least one common enemy at year *t*–1 but none at year *t*. We then calculate the positive and negative shock sizes for individual nodes as in the ABM. The same applies for the measures of shock spread and shock magnitude with real-world data. Note that in the ABM we can measure the time it takes the network to return to equilibrium after the shock. This is not possible with real-world data. In the latter case, it is reasonable to assume that shock-related (and aftershock-related) effects take some time to be realized. Therefore, we use a three-year moving average of shock characteristics to estimate how shocks affect real-world alliance networks. Table II presents the measures of the variables we employ for the real-world analyses. A detailed discussion of data sources and measures is relegated to the Online appendix.

Table II. Variables used in real-world analysis of shocks

Variable	*Measure*	*Measured at time*	*Indicator of*	*Data source*	*Level of analysis*
Dependent variables–network metrics					
Alliance degree centrality	No. of allies/(No. of states − 1)	Pre-shock Post-shock	Alliance connectivity	ATOP (Leeds, 2005), COW (Gibler, 2008)	Nodal
Alliance local transitivity	Same as in ABM	Pre-shock Post-shock	Degree of consistency in state's alliance structure (ally of my ally is my ally)	ATOP, COW	Nodal
Dyadic alliance	=1 if states i and j had an alliance at year t, 0 otherwise	Pre-shock Post-shock	Presence/absence of an alliance between states	ATOP, COW	Dyadic
Structural equivalence	Correlation between alliance profiles of states i and j at time t.	Pre-shock Post-shock	Structural affinity – degree of similarity in alliance profiles of dyad members	ATOP, COW, Maoz et al. (2006)	Dyadic
Density	Same as in ABM	Pre-shock Post shock		ATOP, COW	Network
Transitivity	Same as in ABM	Pre-shock Post shock	Degree of consistency in the alliance network (allies of allies are allies)	ATOP, COW	Network
Avg. path length	Same as in ABM	Pre-shock Post shock	Average distance between states in terms of alliance relations	ATOP, COW	Network
Independent variables–shock characteristics					
Shock spread	Three-year moving average of proportion of states that had changed at least one enemy-of-enemy designation from year t–1 to t.	Post-shock	Measures the degree of change in designations, typically as a result of conflict spread in the system	Dyadic MID data (Maoz, 2005)	Nodal, dyadic, network
Positive shock size	Positive shock = 1 if enemy of enemy = 1 at year t and 0 at year t–1, and 0 otherwise (three-year moving average) $PSS_i = \frac{(\text{No. positive shocks})_{it}}{(\text{Preshock no. of enemies of enemies})_{it}}$	Post-shock	Same interpretation as in ABM	Dyadic MID data	Nodal
Negative shock size	Negative shock = 1 if enemy of enemy = 0 at year t and 1 at year t–1, and 0 otherwise (three-year moving average) $NSS_i = \frac{(\text{No. of negative shocks})_{it}}{(\text{Preshock no. of enemies of enemies})_{i(t-1)}}$	Post-shock	Same interpretation as in ABM	Dyadic MID data	Nodal
Dyadic shock	Same as in ABM	Post-shock	Same interpretation as in ABM	Dyadic MID data	Dyadic

(continued)

Table II. (continued)

Variable	*Measure*	*Measured at time*	*Indicator of*	*Data source*	*Level of analysis*
Control variables					
Democracy	= 1 if Polity Democ > 6, 0 otherwise – monadic = 1 if both states democracies, 0 otherwise – dyadic; Prop. of democratic dyads in system	Pre-shock Post-shock	Democratic state/ dyad	Polity IV (Marshall, Jaggers & Gurr, 2010)	Nodal, dyadic, network
Average cultural similarity w. SRG	Average cultural similarity between focal state and SRG, degree of cultural similarity in dyad	Pre-shock Post-shock	Religious/linguistic similarity between focal state and SRG members; similarity between dyad members	Maoz (2010), Maoz & Henderson (2013)	Nodal, dyadic
Common enemy	1 if states *i* and *j* shared at least one common enemy, zero otherwise	Pre-shock Post-shock	Common interests	Maoz (2005)	Dyadic
U_{ij}, U_{ji}	Utility for alliance formation	Pre-shock Post-shock	Defined the same as in ABM (Eq. 4).		Dyadic, averaged for nodal analysis
National capabilities	CINC score of state; CINC ratio of strongest to weakest member of dyad	Pre-shock Post-shock	Capability score of state, Ratio of capability scores of dyad	COW (2008)	Nodal, dyadic
Size of SRG SRG members	Nodal: no. of states that are in the focal state's SRG Dyadic: 1 = SRG members, 0 otherwise	Pre-shock Post-shock	Degree of security challenge faced by the focal state	Maoz (2010)	Nodal, dyadic
Average no. of MIDs as target	Moving average of the number of MIDs state was targeted	Pre-shock Post-shock	Risk of MID involvement – measure of potential disincentive to form an alliance with state	Maoz (2005)	Nodal
Dyad status	0 = both minor powers, 1 = one regional power and one minor, 2 = one major and one minor, 3 = one major and one regional, 4 = both major powers	Pre-shock Post-shock	Status of dyad members	Maoz (2010)	Dyadic
Log distance	Log of distance (KMs) between capitals	Pre-shock = post-shock	Geographic distance between dyad members	Gleditsch & Ward (2001)	Dyadic
Network effects	Same as in ABM	Post-shock	Effect of network structure on dyadic edges		Dyadic
Capability concentration	Degree of capability dispersion in the international system		See Online appendix	Ray & Singer (1973)	Network

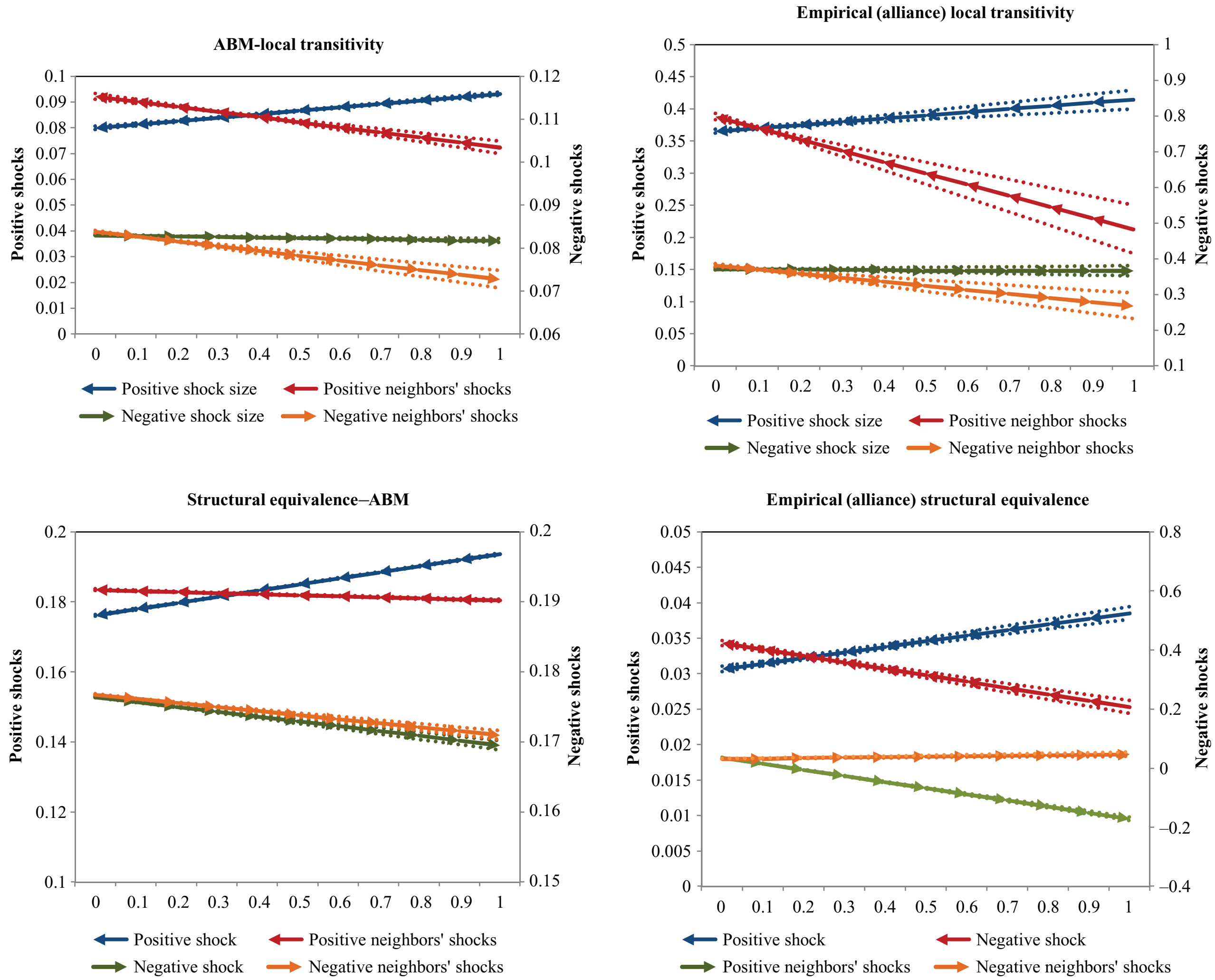

Figure 3. Marginal effects of shock attributes on network characteristics

Left Y axis on each panel measures the marginal effect of positive shocks (or positive neighborhood shocks); right Y axis measures the marginal effects of negative shocks. The central (solid or dashed) lines are marginal effects (arrows reference the relevant Y axis); dotted lines are 95% confidence intervals. Dashed central lines indicate insignificant effects.

Pos. shock size = Positive shock size; Neg. shock size = Negative shock size; Neigh. pos. shock = Positive shock size of focal state's allies; Neigh. neg. shock=Negative shock size of focal state's allies.

Results

In the interest of space, we present graphical summaries of the results comparing the effects of shocks on random networks produced by the ABM and the effects of similar shocks on alliance networks over the period 1816–2010. The results presented here focus on the effects of shock characteristics on network consistency, a less intuitive feature of network structure. However, the discussion also covers shock-related effects on network connectivity. This discussion relies on the full tabular analyses – including the various control variables and analyses of network connectivity – which are presented in the Online appendix. This appendix also discusses the results comparing the treatment to the control (unshocked) networks in the ABM.

Figure 3 presents the results of the analyses of nodal and dyadic reorganization processes. The left panels in the figure represent the results of the ABM; the right panels provide the results of parallel analyses on the empirical alliance network. First, we discuss the results of the ABM. Consistent with our expectations, positive shocks increase nodal and dyadic connectivity (centrality, edges: see Online appendix) and consistency (local transitivity and dyadic structural equivalence). Negative shocks reduce nodal and dyadic connectivity and consistency. Similarly, positive neighborhood shocks reduce connectivity and consistency. Negative neighborhood shocks increase consistency, but – contrary to our expectations – also reduce dyadic connectivity. Overall, however, the results of the ABM match our expectations about the effects of shocks on network reorganization.

Turning to the real-world analyses, the first important thing to point out is that shocks that alter states' strategic environments have significant effects on changes in alliance structures. Positive shocks increase alliance connectivity and consistency. Positive neighborhood shocks reduce alliance connectivity at the nodal and dyadic level. These results match both the ABM and our expectations. Negative shocks, however, do not have a significant impact on connectivity or consistency at the nodal and dyadic level. Negative shocks also reduce nodal connectivity but increase dyadic connectivity. The former result is consistent with the ABM but does not align with our expectations. The latter result is inconsistent with the ABM but matches our theoretical expectations.

In general, the match between the empirical results and the expectations at the nodal and dyadic levels is quite good, considering the murky nature of the empirical data and the complexity of modeling network evolution in a setting that does not really settle into some type of equilibrium. The match between the empirical results and the ABM is far from perfect, but considering the fundamental differences between the stable and controlled environment in the ABM and the empirical world, this match is quite encouraging.

We now turn to the analyses of the effects of shock magnitudes on network structure; the results are in Figure 4. The results of the ABM suggest that positive shock magnitudes increase network density and network consistency (clustering coefficient). The empirical results suggest a similar increase in density as a function of positive shock magnitude. However, the effect of negative shock magnitudes on network connectivity and consistency is not statistically significant. By contrast, negative shock magnitudes tend to increase the connectivity and consistency of alliance networks. This contrasts with our expectations and with the results of the ABM. However, the overall results suggest that shocks have significant effects on the way alliance networks reorganize. Both greater convergence of interests (measured as positive shocks) and greater divergence of interests (measured as negative shocks) cause states to develop increasingly consistent networks by forming transitive alliances. Positive shocks tend to increase alliance network connectivity. In the case of negative shocks, this increase is not statistically significant, but the change is in the expected direction.

Overall, several key points emerge from these analyses.

(1) Shocks that cause dramatic changes in the structure of the security environment of states have significant impact on network restructuring. These effects cut across levels of the network, from the nodal and dyadic levels to the systemic level.
(2) For the most part, direct effects of shocks on the nodes and dyads that experience them are consistent with our expectations: positive shocks increase interest convergence and network connectivity and consistency; negative shocks tend to reduce connectivity and consistency. While these results are not robust, they suggest future research directions.
(3) Individual states and dyads are sensitive not only to shocks they themselves experience, but also to shocks of their network neighbors. In general, we find that neighborhood shocks tend to have a negative impact on network connectivity and consistency.
(4) Notable exceptions do exist, however, and these apply both to the results of the ABM and to real-world alliance networks. The increase in local transitivity following negative shocks in the real-world alliance networks seems to suggest that when states lose potential allies they tighten their existing alliance structures, making them increasingly consistent. This result contrasts with the results of the ABM and with our theoretical expectations. Also, neighborhood shocks have a dampening effect on network connectivity and consistency regardless of the type of shock. The mechanism of this particular effect requires further scrutiny.
(5) The comparison of treatment and control (unshocked) networks in the ABM suggests that networks return to their pre-shock structure even if they have undergone shocks that reduce interest convergence. When shocks increase interest convergence, network connectivity and consistency increase compared to the control networks. Similar patterns are suggested by the results of the empirical analyses, although this requires more focused scrutiny in subsequent research.

Conclusion

The key takeaway of this study is that changes in the structure of states' strategic environments effect significant changes in their perceptions of interests – in particular,

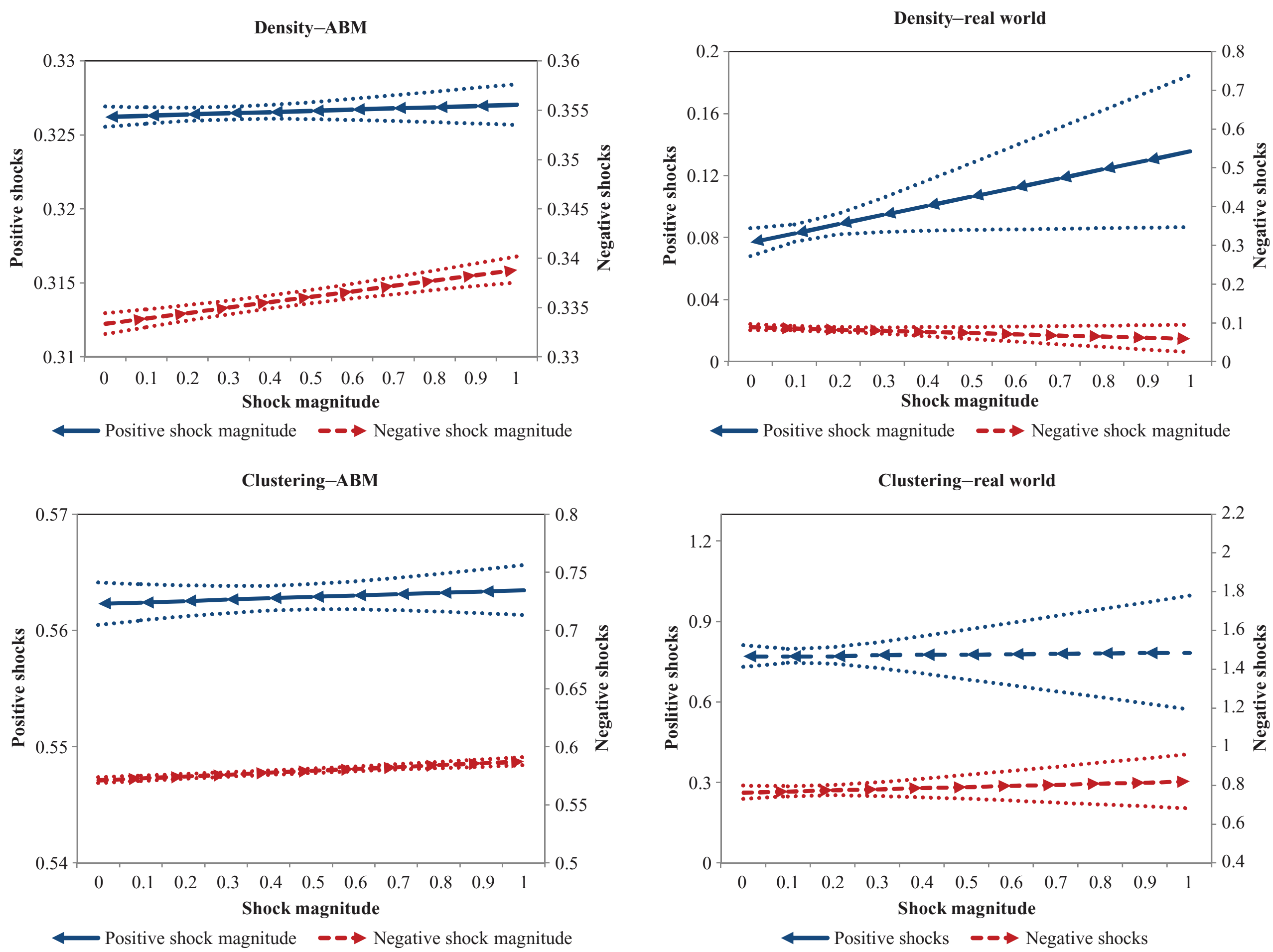

Figure 4. Effects of shock magnitude on network characteristics

Left Y axis on each panel measures the marginal effect of positive shocks (or positive neighborhood shocks); right Y axis measures the marginal effects of negative shocks. The central (solid or dashed) lines are marginal effects (arrows reference the relevant Y axis); dotted lines are 95% confidence intervals. Dashed central lines indicate insignificant effects.

Pos. shock size = Positive shock size; Neg. shock size = Negative shock size; Neigh. pos. shock = Positive shock size of focal state's allies; Neigh. neg. shock=Negative shock size of focal state's allies.

their identification of potential alliance partners. Such environmental changes lead to significant shifts in the connectivity and consistency of alliance networks. The logic underlying such shifts and the networked consequences of such shocks have been modeled via an ABM of network evolution, and the implications of the ABM were tested on real-world alliance networks over the period 1816–2010.

Several points emerge from this study. First, an important insight from the correspondence between the underlying structure of the ABM and the real-world networks concerns the conversion of the homophily parameters into utility functions. As the results in the Online appendix demonstrate, the assignment of weights to the components of the homophily generated utility functions help increase – in most cases quite significantly – the fit of the model compared to the baseline models that rely on the separate homophily components. This improvement in fit is also due to the fact that the utility function incorporates both first- and second-order elements and cost terms.

Second, and related to the previous point, the homophily function suggests that democratic states and autocratic states use the same factors to rate potential alliance partners. However, democracies weigh these factors differently than autocracies, assigning the common regime factor a higher priority than the common interest factor. We find that the impact of democratic homophily on alliance ties – a fact that is well known in the alliance literature – is also meaningful in the sense that shocks tend to have a stronger effect on realignment patterns of democracies compared to autocracies.

Third, the comparison between the ABM results and the real-world effects of shocks reveals some important parallels at the nodal, dyadic, and network levels.

However, there are also some substantial differences. In addition, several patterns emerging from the ABM differ from the theoretical expectations. This suggests that complex network dynamics may yield unexpected results. Note, in particular, how neighborhood shocks affect nodal and dyadic network attributes; specifically, both positive and negative neighborhood shocks tend to decrease nodal and dyadic connectivity and transitivity.

Some of the reasons for the difference between the ABM results and the real-world patterns may be due to fundamental differences between the stylized processes of network evolution simulated by the ABM, and the messy processes that characterize the real world. In the ABM we examine networks at equilibrium (or a fairly stationary rewiring process). The real world does not offer an equivalent to a static equilibrium; shocks happen all the time, and therefore network reorganization is dynamic.

We also assumed that when a shock disrupts the strategic environment of states, states make adjustments, and these adjustments follow the pre-shock tie-formation rules. This is an important insight about how networks react to shocks that affect the strategic environment of states. The general similarity between the ABM results and the real-world patterns suggest that states do not change the principles that define their strategic cooperation choices, even when they are confronted by quite profound changes in their strategic environment. Whether this applies to other types of change in states' strategic environments remains to be seen.

We studied a very specific type of shock, one that reflects a fairly common phenomenon in international relations; about 19% of all state-years have involved at least one positive shock and a slightly lower percentage (18.8%) of state years involved a negative shock. In general, 24% of all states experienced at least one type of change in the identity of the enemy of their enemy during their lifetime. However, this is only one of the shocks that states experience, and these results might be specific for this type of shock. Other types of shocks may have dramatically different effects on nodal behavior and on network structure.

Replication data

The datasets, codebooks, do-files covering the empirical analyses, instructions for the ABM runs, and Online appendix can be found at http://www.prio.org/jpr/datasets. The ABM code is available at https://github.com/Hydrologist/msnp.

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References

Axelrod, Robert (1997) *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*. Princeton, NJ: Princeton University Press.

Bazzi, Samuel & Christopher Blattman (2014) Economic shocks and conflict: Evidence from commodity prices. *American Economics Journal: Macroeconomics* 6(4): 1–38.

Brecher, Michael (2008) *International Political Earthquakes*. Ann Arbor, MI: University of Michigan Press.

Bueno de Mesquita, Bruce; Randolph Siverson & Gary Woller (1992) War and the fate of regimes. *American Political Science Review* 86(3): 638–646.

Cederman, Lars-Erik (1997) *Emergent Actors in World Politics: How States and Nations Develop and Dissolve*. Princeton, NJ: Princeton University Press.

Chiozza, Giaccomo & Hein E Goemans (2004) International conflict and the tenure of leaders: Is war still ex post inefficient? *American Journal of Political Science* 48(3): 604–619.

Colgan, Jeff (2013) Domestic revolutionary leaders and international conflict. *World Politics* 65(4): 656–690.

Correlates of War (2008) National Military Capabilities Dataset (http://correlatesofwar.org).

Cranmer, Skyler J; Bruce A Desmarais & Justin H Kirkland (2012) Toward a network theory of alliance formation. *International Interactions* 38(3): 295–324.

Cranmer, Skyler J; Bruce A Desmarais & Elizabeth J Meninga (2012) Complex dependencies in the alliance network. *Conflict Management and Peace Science* 29(3): 279–313.

Diehl, Paul F & Gary Goertz (2000) *War and Peace in International Rivalry*. Ann Arbor, MI: University of Michigan Press.

Gibler, Douglas M (2008) *International Military Alliances, 1648–2008*. Washington, DC: CQ.

Gilpin, Robert (1981) *War and Change in World Politics*. Cambridge: Cambridge University Press.

Gleditsch, Kristian S & Michael D Ward (2001) Measuring space: A minimum distance database. *Journal of Peace Research* 38(4): 749–768.

Goertz, Gary & Paul F Diehl (1995) The initiation and termination of enduring rivalries: The impact of political shocks. *American Journal of Political Science* 39(1): 30–52.

Gowa, Joanne (1999) *The Elusive Democratic Peace*. Princeton, NJ: Princeton University Press.

Haim, Dotan (2016) Alliance networks and trade: The effect of indirect political alliances on bilateral trade flows. *Journal of Peace Research* 53(3): 472–490.
Hull, Peter & Massami Imai (2013) Economic shocks and civil conflict: Evidence from foreign interest rate movements. *Journal of Development Economics* 103(1): 77–89.
Jackson, Matthew O & Asher Wolinsky (1996) A strategic model of social and economic networks. *Journal of Economic Theory* 71(1): 44–74.
Klomp, Jeroen & Erwin Bulte (2013) Climate change, weather shocks, and violent conflict: A critical look at the evidence. *Agricultural Economics* 44(1): 63–78.
Leeds, Brett Ashley (2005) Alliance Treaty Obligations Project (ATOP) Codebook. Rice University (http://atop.rice.edu/home).
Maoz, Zeev (1989) Joining the club of nations: Political development and international conflict, 1816–1976. *International Studies Quarterly* 33(2): 199–231.
Maoz, Zeev (1996) *Domestic Sources of Global Change*. Ann Arbor, MI: University of Michigan Press.
Maoz, Zeev (2005) Dyadic MID Dataset 2.0. (http://maoz.ucdavis.edu).
Maoz, Zeev (2010) *Networks of Nations: The Evolution, Structure, and Impact of International Networks, 1816–2001*. New York: Cambridge University Press.
Maoz, Zeev (2012) Preferential attachment, homophily, and the structure of international networks, 1816–2003. *Conflict Management and Peace Science* 29(3): 341–369.
Maoz, Zeev & Errol A Henderson (2013) The World Religion dataset 1945–2010: Logic, estimates, and trends. *International Interactions* 39(3): 265–291.
Maoz, Zeev; Lesley G Terris, Ranan D Kuperman & Ilan Talmud (2006) Structural equivalence and international conflict, 1816–2001: A network analysis of affinities and conflict. *Journal of Conflict Resolution* 50(5): 664–689.
Marshall, Monty; Keith Jaggers & Ted Robert Gurr (2010) Polity IV Project: Political Regime Characteristics and Transitions, 1800–2010. Center for Systemic Peace (www.systemicpeace.org/polity/polity4.htm).
McPherson, Miller J; Lynn Smith-Lovin & James M Cook (2001) Birds of a feather: Homophily in social networks. *Annual Review of Sociology* 27: 415–444.
Mearsheimer, John J (1994/95) The false promise of international institutions. *International Security* 19(3): 5–49.
Mearsheimer, John J (2001) *The Tragedy of Great Power Politics*. New York: WW Norton.
Miller, John Howard & Scott E Page (2007) *Complex Adaptive Systems: An Introduction to Computational Models of Social Life*. Princeton, NJ: Princeton University Press.
Nel, Philip & Marjolein Righarts (2008) Natural disasters and the risk of violent civil conflict. *International Studies Quarterly* 52(1): 159–185.
Newman, Mark EJ (2003) Mixing patterns in networks. *Physical Review* 67(2): 1–14.
Nielsen, Richard A; Michael G Findley, Zachary S Davis, Tara Candland & Daniel L Nielson (2011) Foreign aid shocks as a cause of violent armed conflict. *American Journal of Political Science* 55(2): 219–232.
Organski, Abramo FK & Jacek Kugler (1980) *The War Ledger*. Chicago, IL: University of Chicago Press.
Ray, James Lee & J David Singer (1973) Measuring the concentration of power in the international system. *Sociological Methods and Research* 1(4): 403–437.
Salehyan, Idean & Cullen S Hendrix (2014) Climate shocks and political violence. *Global Environmental Change – Human and Policy Dimensions* 28: 239–250.
Siverson, Randolph M & Juliann Emmons (1991) Birds of a feather: Democratic political systems and alliance choices in the 20th century. *Journal of Conflict Resolution* 53(2): 285–306.
Snyder, Glenn H (1997) *Alliance Politics*. Ithaca, NY: Cornell University Press.
Starr, Harvey (1991) Democratic dominoes: Diffusion approaches to the spread of democracy in the international system. *Journal of Conflict Resolution* 35(2): 356–381.
Starr, Harvey & Charles Lindborg (2003) Democratic dominoes revisited: The hazards of governmental transitions, 1974–1996. *Journal of Conflict Resolution* 47(4): 490–519.
Walt, Stephen M (1992) Revolution and war. *World Politics* 44(3): 321–368.
Warren, T Camber (2016) Modeling the coevolution of international and domestic institutions: Alliances, democracy, and the complex path to peace. *Journal of Peace Research* 53(3): 424–441.
Wasserman, Stanley & Katherine Faust (1997) *Social Network Analysis: Methods and Applications*. Cambridge: Cambridge University Press.
Watts, Duncan J (2003) *Six Degrees: The Science of a Connected Age*. New York: WW Norton.

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