The Effects of Shocks on International Networks: Reduced Tie-Capacity of States and the Structure of International Trade and Alliance Networks[1]

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Shocks and International Networks

Abstract

We study the effects of shocks on international networks. We develop an agent-based model (ABM) that allows us to: (1) examine two network formation processes that were shown to characterize international networks—preferential attachment and homophily; (2) analyze the properties of such networks at equilibrium; (3) induce shocks that reduce the capacity of nodes to form ties; (4) study how the networks react to these shocks by regenerating themselves in the post-shock period; (5) compare the pre- and post-shock structures of these networks at equilibrium and derive propositions about the relationship between shock type and network structure. We then test the propositions deduced from the ABMs by comparing the effects of shocks on simulated networks to the effect of similar shocks on real-world alliance and trade networks. We discuss the implications of our results for theory and policy.

1. Introduction

Existing research shows that shocks (i.e., sudden and dramatic events) can induce significant changes in, and have important implications for, international relations. Yet we know very little about the causal mechanisms underlying the effects of shocks; about the implications of different types of shocks; and about the degree to which such effects are generalizable. This paper is part of a large-scale, multi-method project on how shocks influence the international system, unpacking both the specific mechanisms and the systemic effects. Our project allows us to formulate and test a range of hypotheses, taking a big step—both theoretically and methodologically—toward explaining and predicting how different international networks respond to shocks.

To motivate our research, consider Figure 1, which shows how shocks (in this case war) influenced the alliance network over the past two centuries. Some wars (e.g., World War II) have a strong, yet brief, spike-like effect on the density of the alliance network (i.e., the proportion of actual alliance ties relative to the number of all possible alliance ties), with network density quickly returning to a roughly stationary equilibrium. However, in terms of alliance polarization (i.e., the extent to which the alliance network approaches strict bipolarity), we see that wars can have a lasting effect, producing a new trend or equilibrium. As a second example, Figure 2 shows the effect of a major economic shock ("Black Tuesday", the stock market crash of 1929 in the United States) on the volume of global trade. The blue line shows the actual (logged) volume of global trade. The red line is an extrapolation of the pre-1929 trade, and represents a hypothetical level of trade that would have been observed had "Black Tuesday" not occurred. This figure shows—holding a great number of things constant—that it took the system more than 50 to return to the projected pre-1929 level of trade growth. Taken together, these examples show that shocks induce dramatic changes in the international system. These examples also call for a better understanding of the ways in which shocks affect the structure of international networks.

Figures 1 and 2 about here

International politics has experienced multiple shocks of a diverse nature. Some shocks are economic (e.g., the stock market crash of 1929), other shocks are political (e.g., the world wars or the fall of empires), and still others are technological (e.g., advances in weapons systems, the internet).

Some of these shocks are, in fact, aftershocks of preceding shocks (e.g., dramatic changes in the size of the international system as a result of empire collapse). There is some existing research on shock-related effects on international relations but this research is limited and has some major problems. In this paper we focus on the following questions:

1. What are the characteristics of network equilibria for different network formation processes?
2. How do shocks affect network re-organization for different network reconstruction processes?
3. What is the relationship between the characteristics of the shock (e.g., spread, severity) and the structure of network re-organization following the shock?

We address these questions in two steps. First, we develop an agent-based model (ABM) that simulates different network formation processes. We examine the pre-shock attributes of these networks at equilibrium. Then we induce a shock and allow the networks to re-organize using the pre-shock rules of network formation. Finally, we compare the pre-shock network characteristics to the post-shock network characteristics. This comparison enables us to deduce propositions on how shocks affect international networks. Second, we subject these propositions to a set of empirical tests on real-world alliance and trade networks. Our analysis allows us to assess not only how long it takes a network to re-organize after a shock, but also how the network re-organizes. Additionally, we can assess how the characteristics of the shock (e.g., its size, spread, and magnitude) affect the re-organization of a network following a shock.

The paper proceeds as follows. The next section reviews the literature on shocks and international relations, as well as the network analytic literature on shock-related effects on physical, economic, and social networks. The third section offers some theoretical ideas on how networks might respond to different kinds of shocks. The fourth section describes the ABM. The fifth section presents the results of simulations of the ABM. The sixth section outlines the research design for the empirical analysis. The seventh section compares the results of the ABM using random network data to the real-world effects of shocks on alliance and trade networks. The final section outlines the implications of the findings of the ABM and the empirical analyses.

2. Shocks and Networks: State-of-the-Art

A network is composed of a set of nodes (e.g., individuals, organizations, states) and a rule that defines the presence or absence of a link between two nodes, its direction, magnitude, and/or sign (Maoz 2010). Networks may be discretionary—links are formed as a result of nodal choices—or non-discretionary—links are defined by some exogenous factor beyond the discretionary choices of nodes. Discretionary international networks include alliances, trade, joint IGO membership, Preferential Trade Agreements (PTA's), foreign aid sent and received, arms transfers, militarized disputes, etc. Non-discretionary networks include cultural (e.g., religious, ethnic, linguistic) networks, neighborhood (contiguity) networks, etc. Network analysis is a science of interactions—a collection of ideas, analytic tools, and models that describe and analyze the formation, evolution, and structure of physical, economic, or social networks. One of the aspects of network analysis that has important practical implications across a wide array of domains is the analysis of how shocks propagate within a single interdependent system, or across multiple systems that are physically (via common nodes) or functionally (via some logical dependence) connected. We provide a brief review of some research focusing on shocks in different types of networks.

Shocks in Physical Networks. Early research on shock-related processes modeled the cascading effects of nodal failure (Albert *et al.* 2000; Watts 2002). Such shocks cause some of the nodes to fail, and/or some of the edges to collapse. These models are based on varying network topologies, and their key results concern the extent to which a given topology is more or less vulnerable to cascades and network failures. One of the central results of such analyses is that scale-free networks are surprisingly resilient (Albert *et al.* 2000; Barabasi *et al.* 1999; Newman 2003), although others dispute this claim (e.g., Centola 2009). A key issue in the modeling of shock effects concerns the determination of the vulnerability of a given node to failure. Some research examines this vulnerability in terms of a probability distribution that is based on the number of failed nodes in the neighborhood of a focal node (e.g., Watts 2002). Other research simulates this probability using various distributional assumptions (e.g., Holme and Kim 2002).

By definition, each link in a network connects a pair of nodes, allowing for direct interaction between them. If a pair of nodes is not directly connected, they may still be able to interact via links passing through intermediary nodes. Each closed set of reachable nodes is considered a distinct *component*. A fundamental consideration in any network is the number and sizes of distinct components. This is the domain of *percolation theory*, which allows analytic estimates of expected component sizes given basic properties such as the distribution of connectivity among the nodes. Percolation theory has provided the underpinning to studies of connectivity resilience in isolated networks. Using these tools, researchers have been able to model the effects of node and edge failures (Callaway 2000; Cohen 2000), as well as the epidemic spreading of viruses and ideas (Pastor-Satorras 2001). Watts (2002) provides a model that focuses on neighborhood effects on cascade processes that accurately captures cascades of product adoption and influence in networks.

Recent research using complex network analysis has analyzed empirical data on shocks, mostly through the use of cellular phone data (Bagrow *et al.* 2011; Brockman *et al.* 2011). This research begins to identify how the social response to emergencies stresses communication and transportation networks, and will inform our agent-based model.

Social and Economic Networks. Economists who study the effects of shocks on financial networks show how small shocks can propagate through such networks, causing a great deal of damage (Allen and Gale 2000; Count and Bouchaud 2000). Incomplete economic networks stabilize quickly if strong hubs act as circuit breakers that slow down contagion (Gale and Kariv 2007; Kelly and Grada 2000; Leitner 2005). In some cases, an inverted power law helps account for post-shock contagion (Count and Bouchaud 2000). Some interesting ideas on how to minimize contagion in financial systems due to endogenous shocks emerge from historical reviews of financial crises (Tirole 2002).[2]

In terms of organizational research, Uzzi (1997) argued that firm-embeddedness in inter-firm networks increases Pareto-efficiency within firms but exposes firms to higher shock effects. Watts (2004) compares cascades in random, memory-free networks to contagion processes in social networks that contain some degree of memory, showing that in the latter network propagation has threshold effects. Eguiluz *et al.* (2005) and Zimmerman *et al.* (2005) study patterns of cooperation and defection in adaptive social networks. Using computer simulations, these studies demonstrate changes in patterns of cooperation and defection due to global cascades. However, there are relatively few attempts to validate many of these models via empirical analyses that compare the principal deductions of these models to patterns of network adaptation following shocks.

International Networks. The idea that shocks have significant effects on international processes is not new. Economic shocks can have a profound ripple effect on the economics and politics of the entire international system (Maoz 2010: 3). Shocks in the form of global wars (e.g., the Napoleonic Wars, World Wars I and II) can have a tremendous effect on the composition of the international system—state formations in Europe, the Middle East, and Asia—on alliances, and on the international political economy (Gilpin 1981; Brecher 2008). Shocks can also wield a powerful effect on the outbreak and termination of international rivalries (Goertz and Diehl 1995; Diehl and Goertz 2000). The fall of empires (Spain in South America in 1823, the Austro-Hungarian and Ottoman empires in 1918, and the Soviet Empire in the late 1980's) had a dramatic effect on the composition of the international system, resulting in state formations, regime changes, and global realignments. And revolutions—such as the Arab Spring in North Africa and the Middle East—have important effects on the frequency and severity of international conflicts (Maoz 1989, 1996; Walt 1992; Colgan 2013).

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2 Jackson (2008, 185-222) provides a good review of both physical and economic models of diffusion and immunization in networks. Centola and Macy (2007) provide a review of contagion in social networks.

Research examining how shocks affect international outcomes suffer from several problems. First, the causal mechanisms underlying these 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). Third, although scholars have offered some theoretical ideas and empirical results connecting different characteristics of the international system to the probability of certain shocks (e.g., polarity affects the probability and magnitude of war; political revolutions and regime changes tend to diffuse spatially, Starr, 1991; Starr and Lindborg 2003), these results are largely inductive. Fourth, we know very little about the effect of shocks on an outcome of particular importance: the structure of cooperative international networks of different types.

Research on shocks in network science has provided important results about network resilience and network design. Yet, this research has several problems. First, models of cascades studied across disciplines do not incorporate different network formation processes. Second, most research pays little or no attention to the process of network re-organization following shocks, and thus, to the difference between the pre- and post-shock network characteristics, although some research examines the time it takes the network to return to equilibrium.[3] Third, some of the most common models of cascades bear little relevance for international relations. In international relations, if we consider states as nodes, then there are relatively few instances of permanent state collapse. What we do observe with some meaningful frequency is that some states, due to internal or external circumstances, lose some of their capacity to form ties with other states. For example, negative economic growth may force states to drop some of their trading partners. Similarly, a relative decline in military capability may force states to drop alliance partners. State failure is a rare case of shocks that affect networks. As a result, we focus on shocks that cause a reduction in the capacity of some states to form ties. We also examine whether the way in which networks reorganize following shocks differs depending on the network formation process.

3. Preliminary Ideas about Shocks and International Networks

Since we lack a clear theoretical foundation on shocks and shock-related effects on 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. We are aware that this is a simplifying assumption, as most of the shocks that we model herein are endogenous to networks. We plan to relax this assumption after we gain a better understanding of the processes that may cause nodes and/or edges in a network to fail following an exogenous shock.[4]

The assumptions that guide our investigation of shocks and international networks are:

1. *Networks are emergent structures.* Many international networks are discretionary; they form and evolve as a result of the choices of agents to form links with one another. In order to understand how networks form, evolve, change, and react to shocks, we need to develop a model that ex-

[3] See Jackson (2008) for a review of some models.

[4] Some of our other assumptions are more plausible than others. As we gain more knowledge of the processes at work, we may well alter these assumptions.

plains: (a) the criteria by which agents choose partners, and (b) why agents choose to form certain types of links with other agents. The model allows us to connect these choices to the re-resulting structural characteristics of networks.
2. *Agents' calculations of tie-formation and their choice of partners vary by domain*. The logic that drives states to form alliances is not the same as the one that drives them to form trade agreements, or to join international organizations. This difference implies the need for different network formation models. These models may share some common elements, but they have different logical underpinnings. As a result, different networks may have different structural characteristics.
3. *All agents use the same set of rules to decide whether and with whom to form ties*. Some models of network formation allow variation in the rules that nodes use to guide tie-formation. We do not make this assumption because we do not have evidence that it applies to international networks.
4. *Shocks induce a sudden and dramatic change in actors' attributes*. In the present study we focus on shocks that reduce the capacity of one or more nodes to form ties. This shock affects the ability of actor's to form ties.[5]
5. *Shocks do not alter the calculus of tie-formation or the logic of choosing partners*. The reasons that agents form ties, or the criteria by which they choose partners are not altered by shocks. Shocks change the identity of agents, their attributes, or their number. Therefore, understanding how shocks affect networks requires an explanation of how agents adapt to those changes.[6]
6. *Modeling shock effects requires combining network formation dynamics with characteristics and measures of shocks*. The development of theoretical and empirical knowledge of the effects of shocks on international networks requires a model that (a) uses different network formation models, (b) measures network structures at multiple levels of analysis, and (c) allows for different shock types and shock attributes. This makes the combination of agent-based modeling and network analysis an ideal approach for this task.

Our model consists of several parts. First, states have a set of rules that determine when and under what conditions they form ties with other states. These rules vary for different network formation processes. Second, as the network formation process unfolds, states offer to form ties with other states, but a tie is formed only if the target accepts the offer.[7] If an offer is rejected, states turn to other potential partners and this process of offers and responses continues until equilibrium is reached. Equilibrium is reached when no state makes an offer to form a tie or no state can accept an offer to form a tie. We then examine the characteristics of the network at equilibrium. These characteristics are measured at four levels of analysis: nodal (monadic), dyadic, the level of endogenous groups, and the overall network level. These are the pre-shock characteristics of the network equilibrium.

Third, we induce a shock. As noted above, we focus on shocks that reduce nodes' tie-capacity (i.e., the number of edges they can form). The shock is characterized by several key attributes:

1. *Shock Size*. The extent to which a shock affects each node.

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5 In other research, we examine different types of shocks, including shocks that change nodal other attributes, shocks that reduce the size of the network by eliminating some of the agents, or shocks that cause an expansion in the size of the network by introducing new agents.

6 It is possible that shocks lead agents to change the logic of tie formation or of the factors that lead them to choose partners.

7 In some networks, such as conflict networks, ties can be formed unilaterally: targets of violent challenges need not agree for a conflict to happen.

2. *Shock Spread*. The proportion of nodes experiencing the shock.
3. *Shock Magnitude*. The product of shock size and shock spread.

We vary the shock attributes to enable assessment of the relationship between shock attributes and pre-to-post shock changes in network characteristics.

Fourth, after we implement the shock, we restart the network formation process. The nodes that are affected by the shock now reexamine their relations with the nodes to which they are tied. Nodes whose tie capacity is reduced drop some of their ties; nodes that have been dropped and are below their tie-capacity seek to form new ties. The rules that govern these changes are the same as those that guide the pre-shock network formation process. As in the pre-shock network formation process, we run the post-shock network formation process until equilibrium is reached. At this point, we compare the characteristics of the post-shock network to those of the pre-shock network.

The intuition is straightforward. States' choice of partners is based on utility calculations. A given state would typically rank potential partners in terms of the extent to which they need these partners and in terms of what these partners bring to the table. The higher the utility state *i* attaches to state *j,* the more likely the former will offer a link to the latter. This calculus drives the network formation process. What distinguishes different types of network formation processes are the elements that go into the utility functions. In the case of preferential attachment, the centrality of the would-be partner is the key element that determines utility. In this network formation process, states would generally assign a higher utility to more central states than less-central ones. In homophily network formation process, states assign higher utility to states that are similar to themselves (in terms of attributes such as regime type, common enemies, cultural similarity) than to states that are relatively different.

States, which due to a domestic or international event lose some of their capacity (or their motivation) to form ties, need to decide which partners to drop. The factors that affect which ties are dropped are the same as those that affected their choices to form ties in the first place (i.e., ties in the pre-shock network). In other words, a state that had its tie capacity reduced is more likely to drop low-utility ties than high-utility ones.

Once the process of dropping partners has occurred, those states that lost some of their allies or trading partners now need to find other partners for cooperation. The process by which states select new partners is guided by the same utility calculations that governed their pre-shock choice of partners. Thus, the process of network re-organization following a shock is the same as before the shock. What remains to be seen, however, is the extent to which a shock of varying size, spread, and magnitude, alter the structure of networks.

As noted above, we do not have any *ex ante* theoretical foundation to develop expectations concerning the relations between the attributes of shocks and the difference between the characteristics of the network before the shock and those characteristics after the shock. As a result, we use the agent-based model to establish some general results. These results lead to propositions about how shocks affect real-world international networks. We then compare the results of shocks on simulated networks to real-world shocks in international networks.

4. Agent-Based Model of Shocks and International Networks

Agent-based modeling (ABM) is particularly suitable for our enterprise for a number of reasons.[8]

1. *ABM's enable analysis of complex systems*. In our case, complexity arises not only due to the number of agents (nodes) and the number of possible ties among them but also because of the interaction of various shock types with different network formation processes. ABM's allow modeling network formation and network dynamics within a controlled environment in terms of the initial conditions of the network and the characteristics of the shocks. The large parameter space produced by the various combinations of network sizes, shock types, and network formation process make traditional analytic approaches intractable.
2. *ABM's allow the examination of counterfactuals*. These counterfactuals not only explain what happened but also allow for a better understanding of the difference between the empirical and alternative realities that could have emerged.
3. *ABM's enable systematic process tracing*. Most statistical models estimate the relationship between one or more independent variables and a dependent variable. This hypothesized relationship can be derived inductively or deductively (e.g., from a formal model). In the statistical model, the left-hand side is the expected outcome of the hypothesized process (e.g., war/no war, level of trade, compliance with a treaty), and the right hand side is a set of independent variables that are expected to affect the outcome. In practice, these models estimate an input-output relationship. 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 the relationship. Nor does this kind of model actually test the underlying causal process. ABM's actually model the process that links a set of inputs to a set of outputs. If, instead of using simulated data (as we do here), we use real-world data (as we plan on doing in the future), we can then test the relationship between the outputs produced by the ABM and the real-world processes they are supposed to model. A good fit between the ABM output that relies on real-world inputs and the actual events or processes it models not only provides evidence for the existence of a relationship, but also for the validity of the process that produced the relationship.

The basic logic of the model is as follows: each node has an opportunity to form a tie with other nodes, in which case a network is formed.[9] Each node has a tie capacity that dictates how many ties it can form. The tie capacity of nodes in the ABM varies between 0 (isolates) to 70% of the nodes in the network. The tie capacity is randomly drawn from a uniform distribution on the interval [0,70]. The tie capacity is heterogeneous across nodes; some nodes have low, some medium, and some a high tie capacity.

We use two well-known network formation models: preferential attachment and homophily (Maoz 2012). The preferential attachment (PA) model assumes that ties are based on node popularity: the probability that a new node would form a tie with an existing node is a function of the degree centrality (popularity) of the latter. Homophily models assume that the choices of partners depend on

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8 The ABM is programmed in Java using the JUNG (Java Universal Network/Graph Framework) software library. A discussion of ABM's and their advantages and disadvantages can be found in Axelrod (1997), Cederman (1997), Epstein (2006), and Miller and Page (2007).

9 These networks are undirected. A tie between nodes *i* and *j* is the same as a tie between nodes *j* and *i*.

the similarity of nodal attributes: birds of a feather flock together. We now discuss how we implemented these models in our ABM.

Preferential Attachment. We start by setting the network size (a parameter we vary in the simulations). We then create an initial network by randomly selecting 10% of the nodes to form ties with each other. Thus, before we begin our network formation processes, some of the nodes have zero, one, or more ties with one or more of the other initial nodes.

As noted above, in a PA model, the probability of a new node forming a tie with an existing node is a function of the degree centrality of the latter. Formally, the probability of a tie between an existing node and the new node is: $p = (d(v)+1)/(|E|+|V|)$, where d is the degree of the node, v is an existing node, $|E|$ is the number of edges currently in the network, and $|V|$ is the number of nodes currently in the network. The number of ties and nodes currently in the network do not include the new node or the other edges that are attaching to it.[10]

At this point, we randomly select a node not in the network and this node offers to form a tie with an existing node, with the most central existing node having the highest probability of receiving this offer.[11] If the existing node has not reached its tie capacity it accepts the offer; otherwise, the selected node attempts to form a tie with the next most central node, and so on until the selected node reaches its tie capacity limit. We then randomly select another node and repeat this process for each agent. The network reaches equilibrium when the tie formation process has terminated for each agent.

Homophily. In the homophily model, the probability of a tie between two nodes is a function of the similarity of their attributes. In international networks, nodal attributes might represent material capability, regime type, culture, common enemies, or past cooperators. We use three binary attributes of homophily: democracy, common enemies (i.e., enemy of my enemy), and culture. We randomly assign these nodal attributes, with 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.[12]

The probability of a tie between two nodes is proportional to their similarity. We posit different tie formation decisions based on regime type (r=democracy and $\bar{r}$=non-democracy):

$$u_{ij} = \begin{cases} 0.5r_j + 0.3e_{ij} + 0.2c_{ij} & if\ i = r \\ 0.1r_j + 0.6e_{ij} + 0.3c_{ij} & if\ i = \bar{r} \end{cases} \tag{1}$$

10 This probability is slightly different from the one presented in Barabasi and Albert (1999), where the probability was p=(degree(v))/(|E|). The JUNG documentation states that "this would have meant that the probability of attachment for any existing isolated vertex would be 0...and uses Lagrangian smoothing to give each existing vertex a positive attachment probability."

11 If the agent selected to make tie offers has multiple agents with the same centrality score, we randomly select one agent to receive the tie offer.

12 These numbers represent the mean number of democracies from 1816 to 2010 using the POLITY IV dataset (Marshall 2011), the mean number of common enemies from 1816 to 2001 using the dyadic MID dataset (Maoz 2005; Maoz et al., 2007), and the mean number of culturally similar states from 1820 to 2010 using a cultural dataset compiled by Phil Schafer and used in a number of empirical studies on culture and conflict (e.g., Henderson 1998; Henderson and Tucker 2001).

where u_{ij} is the utility node *i* has for forming a tie with none *j*, r_j equals 1 if a node is a democracy and 0 otherwise, e_{ij} equals 1 if nodes *i* and *j* share at least one common enemy and 0 otherwise, and c_{ij} equals 1 if nodes *i* and *j* are culturally similar and 0 otherwise. Since all three variables that make up the utility function are symmetrical, the probability of a tie is equal to the utility function ($p(x_{ij}) = u_{ij}$).

Combining the tie capacity for agents with the homophily tie formation process, we allow agents to form ties. As in the PA model, we create an initial network by randomly selecting 10% of the nodes to form ties with each other. At this point, we randomly select a node not in the network and this node offers to form a tie with an existing node with the most similar existing node (i.e., the highest ($p(x_{ij})$) having the highest probability of receiving this offer.[13] If the existing node has not reached its tie capacity it accepts the offer; otherwise, the selected node attempts to form a tie with the next most similar node, and so on until the selected node reaches its tie capacity limit. We then randomly select another node and repeat this process for each agent. The network reaches equilibrium when the tie formation process has terminated for each agent.

Modeling Shocks and Network Re-organization.

Once the PA and homophily models reach equilibrium, we introduce a shock. We model shocks as changes in the tie capacity of a certain percentage of nodes. This type of shock is particularly relevant for networks that form via a PA process, but may also have important effects on networks formed via homophily as well. We vary two dimensions of this shock: the number of nodes that experience the shock (shock spread) and the percent reduction in the tie-capacity of a given node (shock size).

The shock reduces the tie capacity of nodes in the pre-shock network. If a node is shocked, it needs to decide which of their existing ties to drop. For example, if the shock reduces a node's tie capacity by 5 ties, then the node needs to figure out how to drop those 5 ties. In both models, we reverse the network formation process.

In the PA model, a node that experiences the shock has the highest probability of breaking a tie with the least central node to which it is linked, then the next least central node, and so on until it reaches its new post-shock tie capacity. When this process of dropping ties ends, the "dropped" nodes need to choose new partners. In order to find new partners, the dropped nodes repeat the PA process (i.e., attempting to form ties with the most central nodes), until their tie capacity is reached.

In the homophily model we follow a similar process. A node whose tie capacity was reduced drops ties with the least similar nodes to which it is connected. The "dropped" nodes seek to form new ties according to the homophily process (i.e., attempt to form ties with the most similar nodes), until their tie capacity is reached. In both models, the post-shock equilibrium is reached when no nodes change their ties.

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[13] If the agent selected to make tie offers has multiple agents with the same similarity score, we randomly select one agent to receive the tie offer.

5. Computer Simulations and Measures of Network Characteristics

The computer simulations, we vary four parameters: 1) network formation model, 2) network size, 3) shock size (the percentage drop in nodal tie-capacity), and 4) shock spread (the percentage of nodes affected by the shock).[14] Here we provide a general description of the simulation process. This process consists of several stages:

1. We start by assigning a network size that varies between 20 and 200 nodes (simulating roughly the size of the interstate system between 1816-2014).
2. We assign each node a tie-capacity that ranges between zero (isolate) and 70% of the nodes in the network. A node cannot form more ties than its assigned tie-capacity.
3. For a given network size we choose 10% of the nodes at random and allow them to randomly form ties with each other.
4. Once these nodes ended their tie-formation process, we allow additional nodes to enter sequentially. Each new node assigns a utility score to the existing nodes, and ranks them from highest to lowest. (Utilities depend on the network formation model, as discussed above.) It then offers ties to existing nodes starting with the node to which it had assigned the highest utility. If the node to which an offer is made is below its own tie-capacity, the offer is accepted. Otherwise, the offer is rejected. The new node repeats this process of making offers based on utility rankings up to the point it reaches its tie-capacity, or it exhausted all existing nodes.
5. This process continues up to a point where all nodes are in the network and no node makes or accepts additional offers. This is the pre-shock equilibrium.
6. At this point we measure pre-shock network topology through a set of metrics that we discuss below.
7. Once the pre-shock network reached equilibrium, we induce a shock. A certain proportion of the nodes lose some of their tie capacity. The drop in tie capacity could range between zero (in which case the node was not directly affected by the shock, although it can be indirectly affected as discussed below), to one in which the node is forced to drop all of its ties.
8. Nodes whose tie-capacity was reduced decide which ties to drop. This decision making process reverses the tie-formation process. Specifically, tie-dropping proceeds by dropping the nodes with the lowest utility up to the new tie-capacity.
9. Nodes whose ties were dropped, and are below their tie capacities, can now make offers to other nodes to form ties. This process emulates the network formation process as discussed in steps 4-5 above, up to the point where the network reaches equilibrium.
10. At this point we measure again the post-shock network topology, and compare the pre-shock network to the post-shock network.

Network metrics. As noted, we focus on four levels of analysis in studying the differences between pre-shock and post-shock network structure. At each level, we employ two key metrics that form the basis of this comparison. We discuss these metrics in general detail here. A more precise mathematical representation of these metrics is provided in the online appendix.

Nodal Level. We focus here on (1) degree centrality, defined as the number of actual ties per node over the maximum possible ties for that node ($n - 1$, where n is network size), and (2) local transitivi-

[14] A detailed discussion of the simulation process is in the online appendix.

ty, defined as the number of transitive triangles for a given node as a proportion of the total number of possible triangles for that node.

Dyadic Level. Here we focus on (1) changes in ties between nodes, and (2) changes in dyadic structural equivalence scores. Structural equivalence is a correlation between the relational profiles of two nodes with all other nodes in the network.

Community Level. We use the Girvan-Newman (2004) algorithm to extract communities. We employ two statistics to compare pre- and post-shock community structures: (1) modularity coefficients, and (2) community co-membership—the probability of two nodes being in the same community.

Network Level. We use three network structure characteristics: (1) density, the actual sum of edges divided by the possible sum of edges ($n(n-1)$), (2) transitivity, the number of transitive triangles as a proportion of the number of possible transitive triangles ($n(n-1)(n-2)/6$), and (3) average path length, that is, the average length of a path connecting two nodes.

6. **Measuring Shocks in the Real World**

We use two real-world international networks—alliance and trade networks—to examine the extent to which the patterns produced by the ABM match the real world. Real world network metrics are identical to the metrics discussed above. However, the measurement of real-world shocks is more problematic. Changes in nodal degree—even in directed networks—may be due to a number of reasons that have little or nothing to do with shocks operating on these nodes. For example, a state's may lose trading partners not because of some internal change in its capacity to trade, but because its products have become less competitive. Likewise, a state might lose partners due to shocks operating on the latter. This suggests that measuring shocks in terms of changes of nodal degree would be misleading. Thus, real-world drops in tie-capacities require focusing on the factors that affect a state's capacity to form ties. Alternatively, we need to measure shocks in terms of a state's willingness to form ties. We elaborate on this below.

A reduced capacity to trade involves changes in states' productive capacity. This capacity indicates the supply of goods and services that emanates from the state and defines its capacity to export. Likewise, production capacity determines the income available for importing goods and services. A decrease in productive capacity reduces a state's ability to export and import goods. Thus, in trade networks we define a shock as negative economic growth—a drop in per capita GDP. The magnitude of the drop in GDP reflects, therefore, the shock size that a state experiences. For any given year, the proportion of states that experience negative growth then measures the spread of the shock. Shock magnitude is calculated as noted above.

For alliance networks we use a more complex indicator of shock. This indicator involves the motivation to form alliances. Security alliances form a common capability pool. A state needs to form alliances to the extent that it cannot deal with external challenges by using its own military, economic, or political resources. Under such circumstances it would be willing to give up some degree of autonomy in return for increased security that comes through pooling of its allies resources with its own.

Thus, the need for alliances is a function of the gap between the capabilities of the focal state and the cumulative capabilities of its enemies: the higher the gap, the greater the state need for alliances. Our argument is counterintuitive. It contrasts the traditional conception that a shock is an unwanted event. We suggest that a state experiences a security shock that reduces its tie capacity when its need for allies declines. The underlying intuition is that security ties are a child of necessity (Mearsheimer 2001). States are suspicious of each other, and are out to exploit each other. Each state knows that other states are just as suspicious and opportunist as it is. So its natural inclination is to rely on as few other states as possible. When a state's relative capabilities increase, the need for allies declines. When this happens, it would be more willing to drop some of its allies than when its need for allies remains constant or when such a need increases.

Thus, we measure the size of a shock that a state experiences as the percent change in its relative national capabilities from one year to the next. Relative capabilities are measured as an average share in the system resources on six indicators of demographic, economic, and military resources. This is the Combined Index of National Capabilities (CINC) as used by the COW project (COW 2010). The larger the gap between a state's current CINC score and its previous CINC score, the more secure the state is assumed to feel, and the less the need for allies. Under such circumstances, it can afford to drop more allies. A negative change in the state's level of capabilities is assigned a shock size of zero, because we do not examine "positive" shocks—that is, an increase in the demand for allies. We will address this type of shock in subsequent studies.
As in the case of trade shock spread, alliance shock spread is the proportion of states that have experienced a positive shock of any size in a given year.

Estimation.

We use a standard model to estimate shock-related effects on network structure. This model has the following structure:

$$NC = a + bX + \gamma Z + \delta Y + \varepsilon \qquad (2)$$

Where NC is a specific network characteristic, $\mathbf{X}$ is a matrix of control variables, Z is the measure of shock size, Y is a measure of shock spread, and b, γ, and δ are coefficients, and ε is the error term. Note that we include the pre-shock network characteristic as one of the control variables. We also estimate differences in network characteristics such that $\Delta NC = NC_1 - NC_0$, where the subscripts reflect the post- and pre-shock value of *NC*, respectively. Detailed discussion of the control variables, as well as the results based on differences are provided in the online appendix.

Estimation at the nodal and dyadic level requires controlling for network effects—the dependence of a given network characteristic on the network characteristics of other nodes or dyads. To control for network effects we employ a method developed by Joyce, Maoz, and Hammond (2014) that relies on expected values (EVs) derived from degree distributions. For the nodal level, network effects are measured by the mean EV of a node's neighbors. For dyadic network effects, we use dyadic EVs, as specified by Joyce *et al* (2014).

6. **Results**

We begin the discussion of results by looking at the effect of shocks on nodal characteristics. Table 1 provides an example of the analyses we have conducted at various levels of analysis. It compares the results of the ABM with the results of the analyses conducted on real-world data. Subsequent results focus only on the effects of shock characteristics.

Table 1 about here

We start the discussion of the results reported in Table 1 by reviewing the effects of the variables that describe the network formation process on the dependent network characteristics. In the case of both the PA and Homophily models, tie-capacity has a positive effect on both centrality and nodal transitivity. In contrast, sequence of entry has a negative impact on these nodal characteristics. The relational attributes of the node (joint democracy, common enemies, and cultural similarity) have no meaningful effect on either nodal centrality or transitivity in the PA model, but have strong positive effect on transitivity in the homophily model. Neighborhood effects are highly significant for both models and for both dependent variables. All these results are consistent with the expectations that derive from the network formation algorithms. The effect of the control variables on trade and alliance centrality and transitivity are generally consistent with previous analyses (e.g., Maoz 2010), so there is no need to elaborate here.

With respect to shock-related effects, the results suggest a surprising, but rather consistent effect. As expected, shock size tends to have a negative impact on nodal centrality and on nodal transitivity. This holds for both the ABM results—regardless of network formation model—and for the empirical networks we studied. However, as shocks spread across the network—nodal centrality and nodal transitivity scores tend to increase as well. Nodes that experienced shocks tend to become less central and less transitive. However, when the spread of shock is high, nodes respond by increasing the number of their ties and forming ties that are increasingly more transitive than during the pre-shock periods. Again, this result holds consistently for random networks—both those that were formed via preferential attachment processes or via homophily processes. It also holds to some extent in real-world networks. Specifically shock spread has a positive effect on trade transitivity and on alliance centrality scores, but not on trade centrality or alliance transitivity.

We turn now to the analysis of shock-related effects on dyadic network characteristics. Figure 3 displays the marginal effects of shock size and shock spread on the probability of dyadic edges and on dyadic structural equivalence. The upper part of the figure shows the results from the ABM using random network data; the lower part shows the results for alliance and trade networks.

Figure 3 about here

In general, the results of the estimates of dyadic network characteristics mirror those of the nodal analyses. The variables representing network formation indicators affect both dyadic edges and dyadic structural equivalence in expected ways. In the analyses of real world networks, the gravity model that is commonly used to explain international trade (e.g., Helpman, Melitz, and Rubinstein 2008, Ward, Ahlquist, and Rozenas 2013) performs according to expectations. The alliance estimates are also in accordance with previous research (Maoz 2010; Cranmer, Desmarais, and Menninga 2012). Again, network effects are quite substantial, supporting prior arguments in the literature (Cranmer and Desmarais 2010) about dyadic dependence in international networks. (Full results are reported in the online appendix.)

The effects of shock characteristics on dyadic edge and dyadic structural equivalence in both PA and Homophily networks are similar to their effects on nodal characteristics: shock size reduces the probability of an edge and of the degree of structural equivalence. However, shock spread tends to increase the probability of an edge and the level of structural equivalence. Comparing shock-related effects on ABMs with random data to the effects of shocks on alliance and trade networks reveals generally similar pattern. In both trade and alliance networks, shock size tends to reduce the probability of an edge (in the case of trade—the level of dyadic trade). Shock size tends to reduce and the degree of structural equivalence in alliance networks but does not have a statistically significant effect on trade structural equivalence. Shock spread tends to have a positive effect on both alliance and trade structural equivalence.

Figure 4 shows the effect of shocks on community characteristics. First, examining the results for the ABM, we see that shock size tends to reduce the probability of any two nodes being in the same community. This applies to both networks. However shock spread tends to reduce the probability of community co-membership in PA networks but increases the probability of community co-membership in homophily networks.

Figure 4 about here

The results for real world networks are mixed. Shocks seem to affect alliance network in the same way that they affect random PA networks in the ABM. Specifically, both shock size and shock spread reduce the probability of alliance community co-membership. However the effects of shocks on trade community co-membership are not statistically significant.

The ABM results suggest that in both PA and Homophily networks, average shock size tends to reduce modularity, which suggests that group differentiation declines as nodes experience more severe shocks. However, as shocks spread, modularity tends to increase. These results, however, are fundamentally different than the effects of shocks on real-world networks. In alliance networks, shock size increases modularity but shock spread does not affect modularity. In contrast, in trade networks neither shock size nor shock spread has a significant impact on modularity scores.

Figure 5 about here

We now turn to a discussion of shock-related effects on the structural characteristics of networks as a whole. As noted above, we focus on three principal characteristics of networks: density, transitivity (clustering coefficient) and average path length. Figure 5 compares the effects of shocks on network structure due to the ABM runs to the effects of real-life shocks on real-world networks. The first point about these results is that shocks affect random networks in the same way regardless of how such networks were formed. Specifically, shocks increase the density of networks as well as the average path length. They also tend to reduce the transitivity of such networks. This applies almost in the same manner to PA networks and to homophily ones.

However the comparison of these effects to the effects of shocks on real-world networks does not work as well as it did for lower levels of analysis. First, as shock magnitude increases, the density of trade networks tends to decline. In contrast, the increase in alliance density tends to be in line with the ABM results. Second, shock magnitudes do not have any statistically significant effect on the transitivity of alliance or trade networks. Finally, shock magnitude has a significant positive effect on the average path length of alliance networks—again in line with the ABM results. On the other hand, shock magnitude does not seem to have a significant effect on the average length of trade networks.

Some general observations emerge from these analyses. First, shocks that affect nodal tie-capacity seem to have similar effects on networks that form via different processes. We qualify this result to the two network formation processes that were analyzed herein. More work is needed to examine whether this effect generalizes to networks that are formed by processes other than the PA or homophily processes. Second, the analysis of random networks via ABMs suggests that shock spread has a surprising effect on network re-organization. Specifically, shock spread increase nodal degree, nodal transitivity, the probability of dyadic edge, the degree of dyadic structural equivalence, and network density. This contrary to what one would expect, namely, shocks that spread widely to have dampening effects on connectivity indicators such as centrality and transitivity at the nodal level, or on the probability of dyadic edge or dyadic structural equivalence. In fact, shock spread tends to have a positive effect on these characteristics. What is also surprising is the fact that shock magnitude has a positive effect on network density.

Some of this puzzle may be explained by the following. First, looking at the general differences between pre- and post-shock networks (Table A4 in the online appendix), we find that shocks generally lead to a significant reduction in nodal degree, nodal transitivity, group co-membership, group modularity, and network density. However, shocks tend to increase dyadic structural equivalence and network transitivity. Without controlling for network effects, shock spread tends to generate similar effects to shock size. However, once we control for network effects, the effects of shock spread on network re-organization seem to be positive in terms of nodal, dyadic, and network connectivity. In general, when we combine shock size with shock spread to produce the shock magnitude statistic, shocks have an adverse effect on network connectivity across network levels and across network formation models.

On the whole, alliance networks seem to respond to shocks that reduce nodal tie capacity in ways that are generally similar to those observed in simulated random networks. This applies across levels of analysis, although not consistently so. The re-organization of trade networks following shocks mirrors similar processes in random networks at the nodal and dyadic levels, but not at the group level or the network level.

Although shocks seem to have similar effects on networks formed via PA or homophily processes, there are some differences between the ways in which these two network types re-organize following shocks. For example, shocks tend to significantly reduce dyadic structural equivalence and community co-membership in PA networks but they increase significantly the same characteristics in homophily networks. Likewise, shocks increase the transitivity of PA networks but reduce the transitivity of homophily networks. More generally, shocks that cause reduction in tie-capacity tend to result in more consistent and more pronounced drops in the connectivity indicators of PA networks than in the same connectivity indicators in homophily networks.

The explanation for these different effects requires understanding of the conditions that characterize equilibria in different network formation models and of the ways shocks affect these equilibria. The type of shock modeled here is more likely to have strong effects in networks where popularity seems to drive network evolution. In such networks, a popular (i.e., central) node can be affected by the shock directly—it experiences a shock that force it to drop some of its edges. Or a node can be affected indirectly—some of its network neighbors are forced to drop their ties with it. In either case, the distribution of popularity scores in the network changes both as a result of the shock, and as a result of the network generation process. In contrast, in homophily networks, nodal attributes—which are important determinants of tie-formation—are not affected by the shock. Here only direct shock effects operate; the network generation process reforms the network in much the same way it existed before in a way that is not affected by the shock per-se. This may explain the differences in the magnitude of effects of shocks between two network types, and also the few differences between the networks in terms of negative (connectivity-reducing) versus positive (connectivity-enhancing) effects in these types of network formation process.

6. Conclusion

This study offers a systematic approach to the study of shock-related effects on international networks. The experimental stimulus in the present study is rather simple: the reduction in tie capacity of a certain proportion of the nodes in the network. As discussed in the introduction, this type of shock enables us to model the effects of major economic crises that reduce the capacity of states to trade due to sharp drop in production and/or drop in its currency values, or the reduced motivation to form alliances due to radical improvement in states' capabilities.

The following results emerge from the analyses conducted herein.

1. Unsurprisingly, shocks that reduce the capacity of nodes to form ties tend to have a negative effect on nodal degree centrality and on nodal transitivity. This result is observed both in simulated networks—whether formed via a PA or a homophily process—and in real-world trade and alliance networks.
2. Likewise, such shocks tend to reduce the probability of dyadic edge and the degree of dyadic structural equivalence. Again, this applies to both types of network formation processes and to alliance networks. Shocks tend to reduce the probability of dyadic edges in trade networks but do not significantly affect trade structural equivalence.
3. Shocks tend to reduce both the probability of group co-membership and group modularity. This applies to both types of network formation processes. Shocks tend to decrease the probability of group co-membership in alliance networks but they tend to increase network modularity. In contrast shocks do not appear to have a noticeable effect on trade community structure.
4. Shocks increase the density and average path length of both PA and homophily networks, but they tend to reduce the transitivity of such networks. Shocks tend to increase the density and path length of alliance networks but they have no noticeable effect on alliance transitivity. In contrast, shocks seem to have no noticeable effects on the characteristics of trade networks.
5. On the whole, PA and homophily tend to respond to shocks in much the same way. Some differences exist between these network formation processes, and these are due probably to the fact that tie-reducing shocks operate on nodal popularity but not on exogenous nodal attributes that affect homophily.
6. The response of real-world networks to shocks is similar to the response of simulated random networks to similar shocks at the nodal and dyadic level. This is true of alliance networks more than of trade networks. In contrast, at the group (community) level and at the

network level as a whole, there are significant differences between the way shocks affect random networks and the way in which they affect real-world networks.

The similarities between shock-related effects in simulated networks and the effects of shocks on real-world networks are encouraging, in part because they lend some credence to the process that was at the basis of the ABM. As noted, this similarity suggests that the dynamics that are captured in the ABM may well help explain how real-world networks respond to similar types of shocks. However, the glass is only half-full. We need to explain both the similarities and the differences between real-world network re-organization following shocks and the restructuring of random networks.

These differences may be due to several factors that distinguish the ABM from real-world processes. First, the definition of shocks in the ABM is very different from those we used to model shocks in alliance and trade networks. Shocks in the ABM were introduced exogenously. In real-world networks shocks are in fact endogenous. Moreover, the way we measured shocks in real-world network is based on some underlying nodal attributes such as GDP and capability changes. Consequently, shock sizes in real world networks were of significantly smaller sizes than in the simulated networks. Although the range of shock spread was similar in the simulated networks and in real-world networks, the sizes of shocks were relatively small. This was, in particular the case for trade networks where drops in GDP averaged less than one percent per year. (The exception is the first few years of the great depression where shock sizes averaged slightly over four percent, with ranges from zero to 0.2.)

Second, in real-world networks it is difficult—if not impossible—to separate short-term from long-term effects of shocks. We focused only on shock-term effects, examining the changes from one year to the next on the structure of networks. This makes the analysis of shocks relatively more manageable. We used in some analyses moving averages of shock attributes to study longer-term effects. The results were not much different from the ones reported here. However, in contrast to our ability to study simulated networks at equilibrium conditions, real world networks do not lend themselves to such operations.

Third, in the ABM we induced "negative" shocks—a reduction in nodal tie-capacity. In the real world, however, shocks can be both "positive" and "negative." Positive shocks can lead to an increase in nodal tie capacity. These "positive changes" may include economic growth that generates greater incentives to trade, or changing strategic circumstances that motivate states to search for additional allies. Negative and positive shocks happen simultaneously, but we did not assess the effects of positive shocks on networks. We leave this for a subsequent study.

There are several innovations in the present study. First, we reasoned that the manner in which different networks re-organize given similar types of shocks depends on the network formation process, that is, on the logic that drives nodal choices of partners. In contrast to previous studies that focus on a specific network formation model, we study different network formation processes. This enables us to assess the way in which shocks affect different network types. The results of the ABM as well as the empirical results suggest that this assumption is only partially correct. The two types of networks studied in the ABM and the two empirical networks investigated exhibit both very similar patterns of network-reorganization on some levels (e.g., nodal, dyadic) and quite different patterns of re-organization on other levels (e.g., communities, network).

Second, in contrast to other studies in network science that focus on the spread of shocks and their propagation through the network, our focus was on network re-organization. Our reasoning is that the effects of shocks are best realized by comparing the structure of the networks before the shock to their post-shock structure. The difference between pre- and post-shock network characteristics, given shock attributes and network formation process, tell us how this re-organization process works. We employ an ABM that simulates the propagation of shocks and the manner in which nodes respond to shocks that they themselves or their neighbors experience. This allows us to identify the consequences of a simulated process of network re-organization.

One possibility we did not discuss extensively here but can be inferred from the results is that shocks affect not only the ability of nodes to form ties, but they can cause changes in the network formation model. For example, nodes that experience shocks may switch from a PA process of tie formation to a homophily process, or vice versa. Suppose this is indeed the case. Surprisingly, then—given the fact that both types of networks react to shocks in similar ways for the most part—the shift in network formation processes does not seem to have noticeable effects on post-shock structure.

Finally, in contrast to several studies employing ABMs to study complex processes both in networks and other structures, we attempted an empirical validation of the patterns emerging from our study of shocks in simulated networks. This validation process has yielded some interesting parallels but also revealed important differences between the "pure" processes that we modeled via the ABMs and the real world networks. The similarities suggest some important insights into network functioning following shocks. The differences between the ABM results and the empirical patterns offer novel ideas about both modeling and empirical analysis of international networks.

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Table 1: The Effect of Shock on Nodal Characteristics—Comparing ABM Results with Trade and Alliance Networks

Independent Variable	ABM			
	Centrality		Local Transitivity	
	PA	HO	PA	HO
Pre-Shock Characteristic	0.456**	0.469**	0.446**	0.451**
	(0.003)	(0.003)	(0.004)	(0.004)
Network Size	1.03e-04**	7.8e-05**	1.52e-04**	1.61e-04**
	(4.27e-06)	(4.48e-06)	(7.2e-06)	(7.08e-06)
Tie Capacity	0.345**	0.396**	0.467**	0.556**
	(0.003)	(0.003)	(0.004)	(0.004)
Sequence of Entry	-1.1e-04**	-6.4e-05**	-2.1e-04**	-2.5e-04**
	(5.07e-06)	(5.05e-06)	(8.99e-06)	(8.31e-06)
No. Joint Democracies	-0.002	-0.005*	0.003	0.011**
	(0.002)	(0.002)	(0.003)	(0.003)
No. Common enemies	4.12e-04	-0.002	-0.003	0.059**
	(0.001)	(0.001)	(0.002)	(0.002)
No. Culturally-Similar States	2.03e-05	2.4e-05	1.5e-05	1.29e-04**
	(1.09e-05)	(1.23e-05)	(1.71e-05)	(1.77e-05)
Network Effects	-0.094**	-0.092**	0.348**	0.28**
	(0.002)	(0.002)	(0.005)	(0.005)
Shock Size	-0.129**	-0.138**	-0.16**	-0.165**
	(0.001)	(0.001)	(0.002)	(0.001)
Shock Spread	0.008**	0.039**	0.062**	0.077**
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.069**	0.042**	-0.208**	-0.187**
	(0.001)	(0.001)	(0.003)	(0.003)
N	68,970	68,970	68,970	68,970
No. Runs per network size	33	33	33	33
F-Statistic	63,532.91	55,883.54	33,599.25	40,480.51
R-Squared	0.921	0.911	0.856	0.867
RMSE	0.043	0.047	0.069	0.071

Independent Variable	Real-World Networks			
	Trade Networks		Alliance Networks	
	Centrality	Transitivity	Centrality	Transitivity
Pre-Shock Characteristic	0.749**	0.789**	0.34**	0.862**
	(0.008)	(0.007)	(0.006)	(0.005)
Regime Score	1.6e-05	8.68e-06	4.21e-05*	3.32e-05
	(1.64e-05)	(2.73e-05)	(1.92e-05)	(3.70e-05)
Regime Stability	-1.1e-04**	7.4e-05	1.77e-04**	2.66e-04**
	(2.52e-05)	(4.1e-05)	(3.57e-05)	(6.44e-05)
Regime in PRIE	1.38e-04**	3.83e-04**	3.48e-04	9.37e-05*
	(3.77e-05)	(6.42e-05)	(1.92e-04)	(4.3e-05)
GDP Per-Capita/ CINC	1.34e-06**	4.86e-06	-0.165**	-0.059
	(1.47e-07)	(2.76e-06)	(0.027)	(0.049)
Past Conflict Involvement	-2.4e-04	-0.001**	-0.001*	-0.002**
	(2.72e-04)	(4.57e-04)	(3.2e-04)	(0.001)
Network Effects	-9.91e-07**	7.42e-07*	1.118**	0.459**
	(2.19e-07)	(3.74e-07)	(0.011)	(0.024)
Shock Size	-0.068**	-0.001	-0.026**	-0.046**
	(0.011)	(0.02)	(0.005)	(0.013)
Shock Spread	0.008	0.022**	0.01*	-0.001
	(0.004)	(0.007)	(0.002)	(0.006)
Constant	0.021**	0.055**	0.052**	0.066**
	(0.001)	(0.003)	(0.001)	(0.004)
Rho	-0.18772	-0.11311	0.390976	0.133421
N	7220	7196	8391	8134
No States	145	145	196	194
F-Statistic	1462.96	1764.78	1956.06	3487.82
R-Squared	0.962	0.912	0.761	0.937

Figure 1.

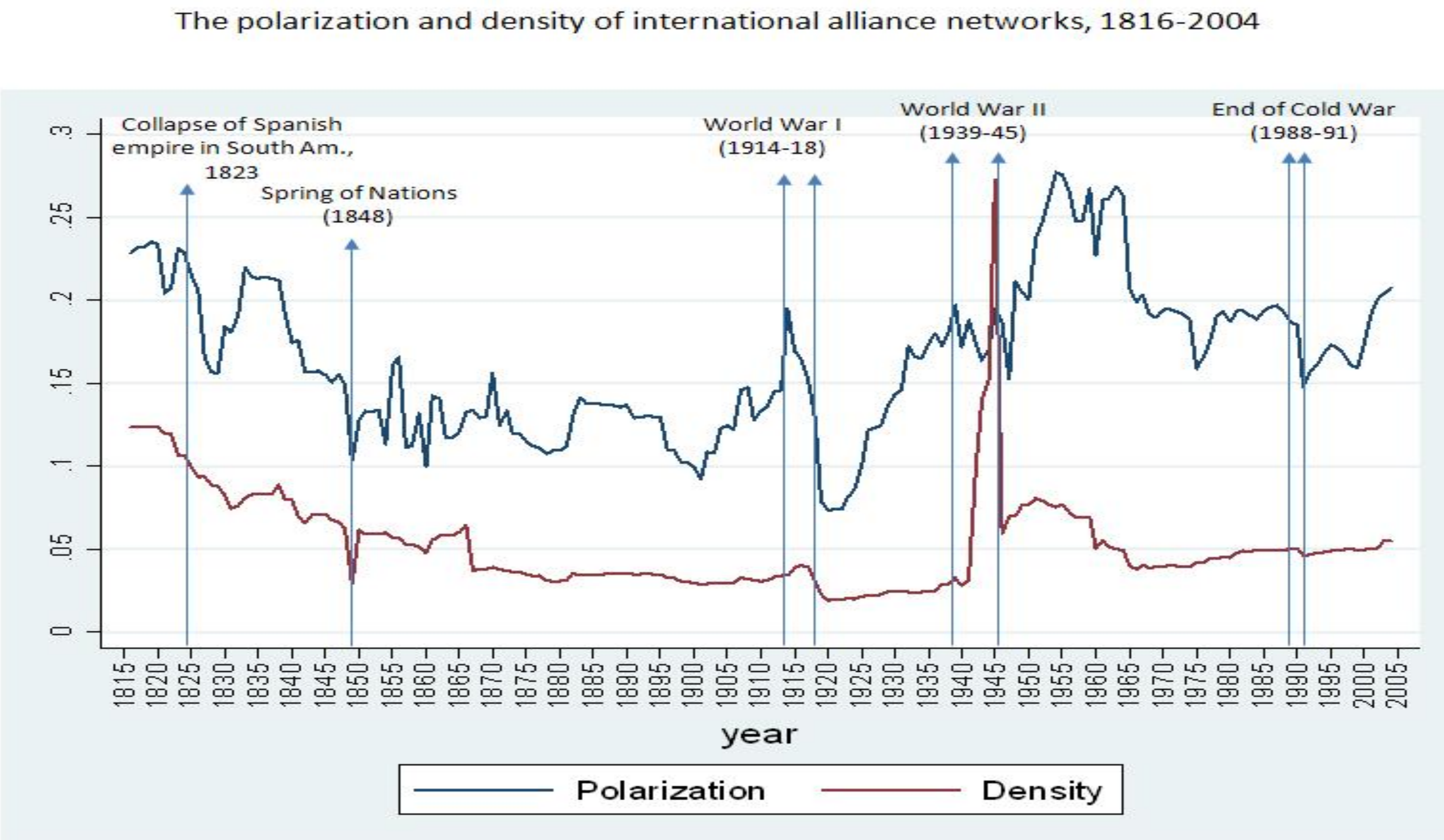
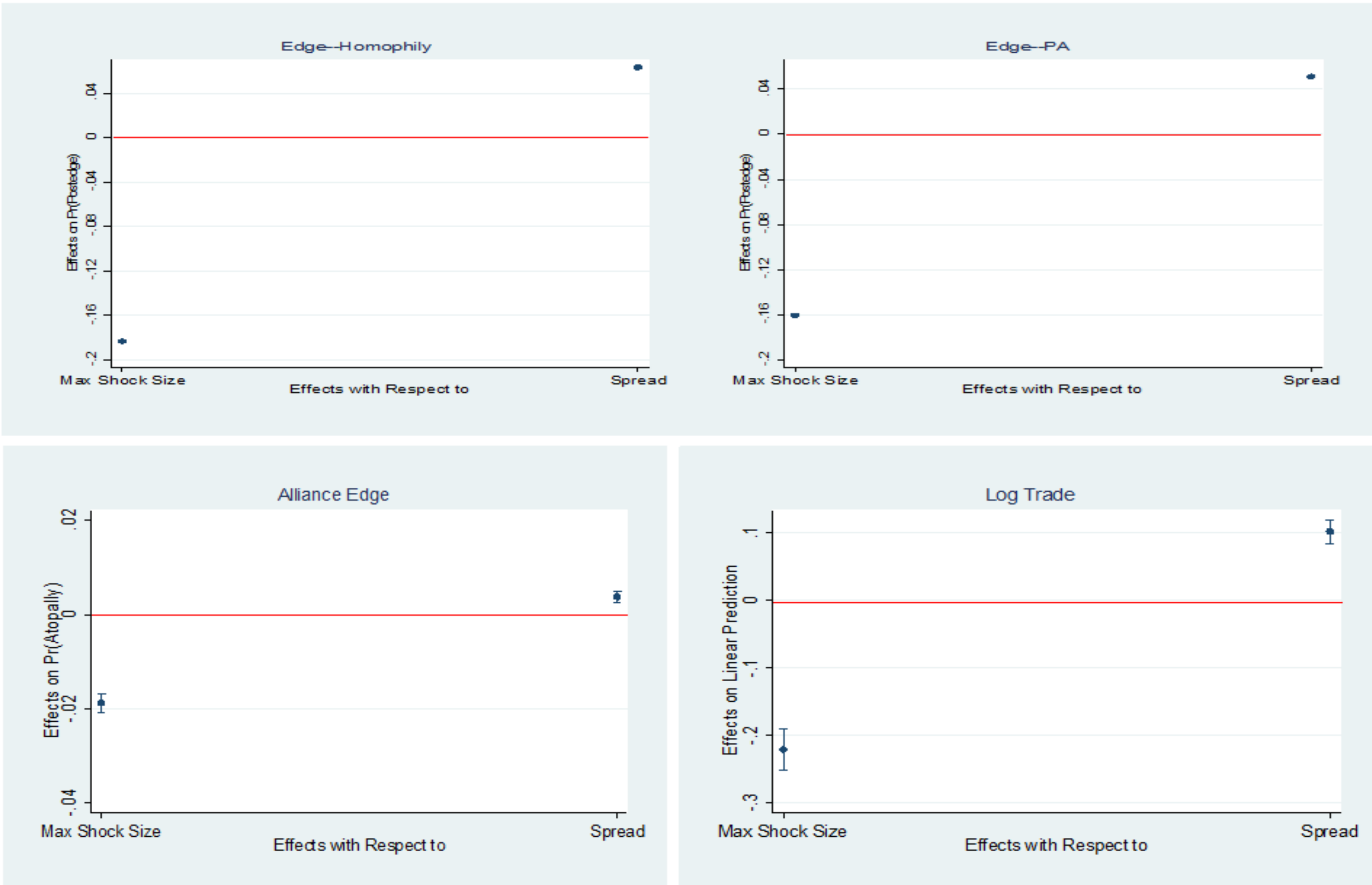

The polarization and density of international alliance networks, 1816-2004
Collapse of Spanish empire in South Am., 1823
Spring of Nations (1848)
World War I (1914-18)
World War II (1939-45)
End of Cold War (1988-91)
0
.05
.1
.15
.2
.25
.3
1815
1820
1825
1830
1835
1840
1845
1850
1855
1860
1865
1870
1875
1880
1885
1890
1895
1900
1905
1910
1915
1920
1925
1930
1935
1940
1945
1950
1955
1960
1965
1970
1975
1980
1985
1990
1995
2000
2005
year
Polarization
Density

Figure 2.

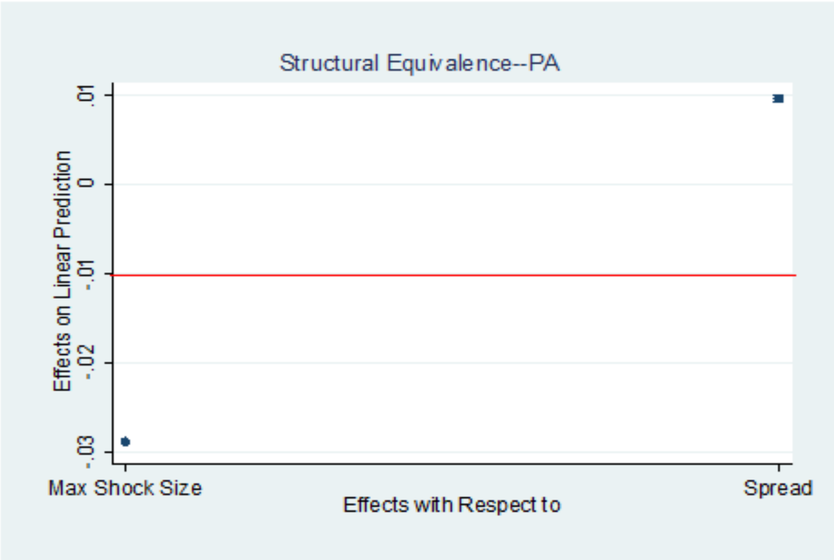

Log World Trade, 1870-2012
Log World Trade
18
16
14
12
10
1870
1880
1890
1900
1910
1920
1930
1940
1950
1960
1970
1980
1990
2000
2010
Year
logtrade
Fitted values

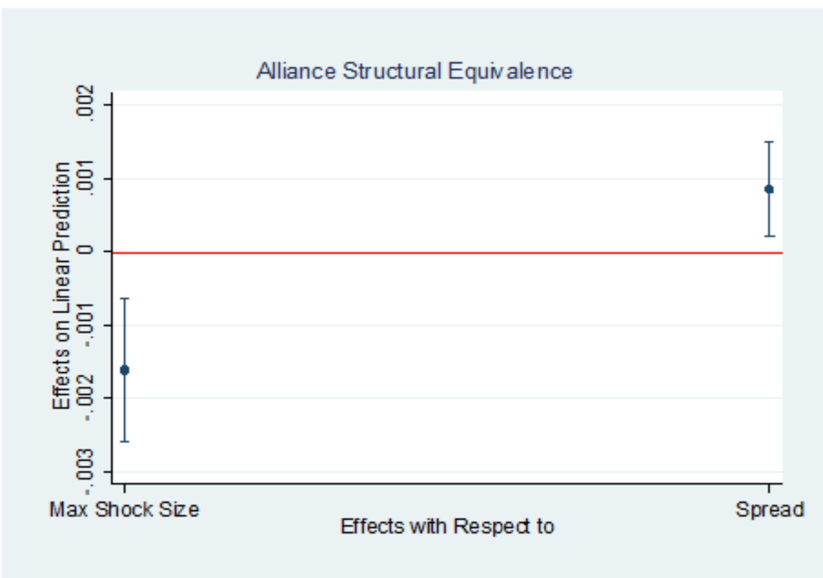
Figure 3: Effects of Shocks on Dyadic Network Characteristics

3.1. Edges



3.2. Structural Equivalence





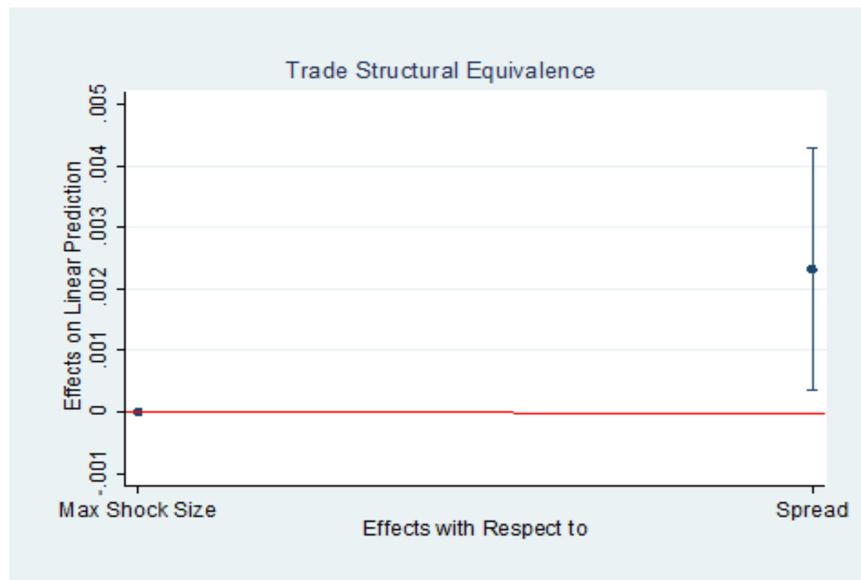
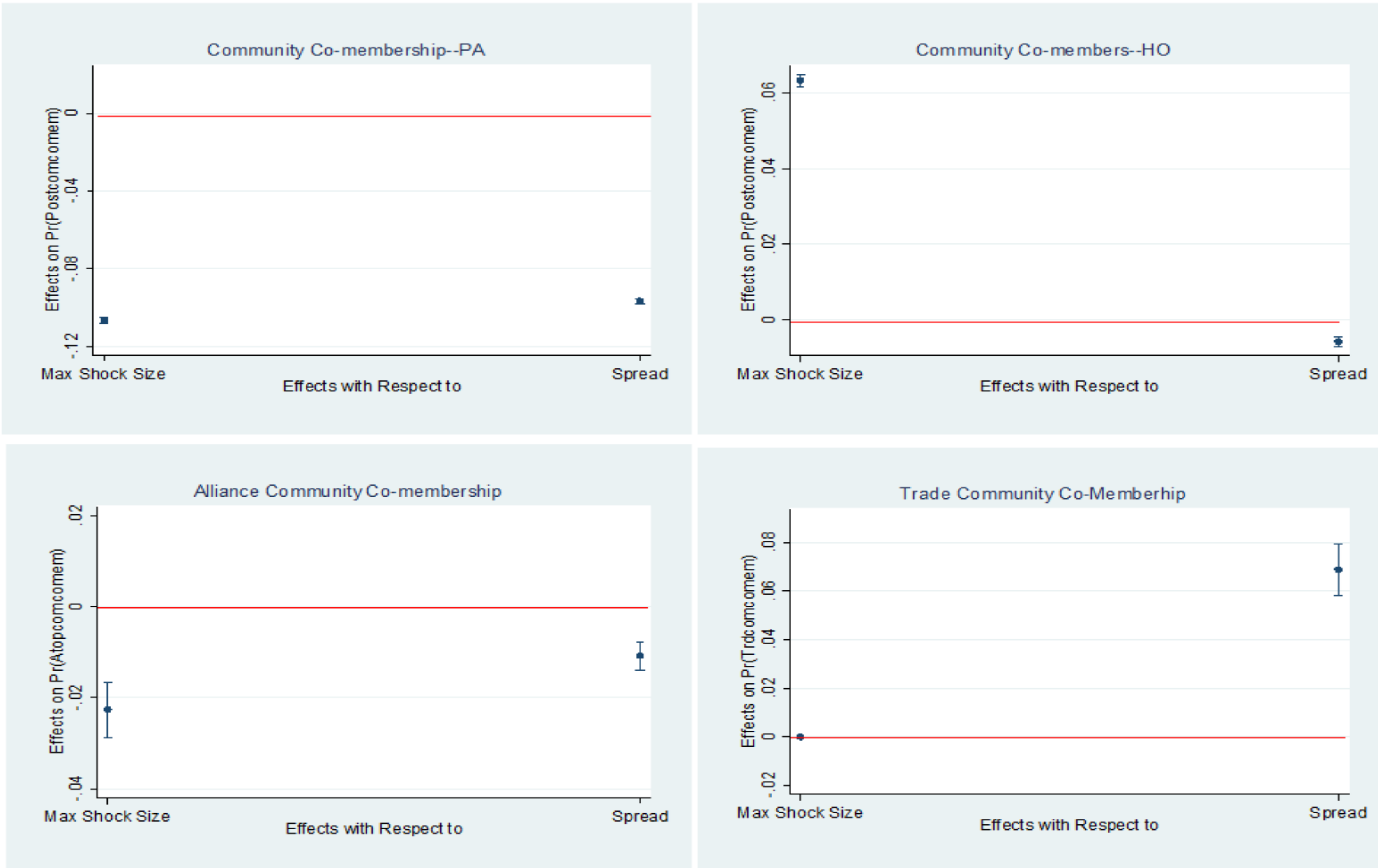


Figure 4: The Effects of Shock Characteristics on Community Structure
4.1. Community Co-Membership



4.2. Modularity

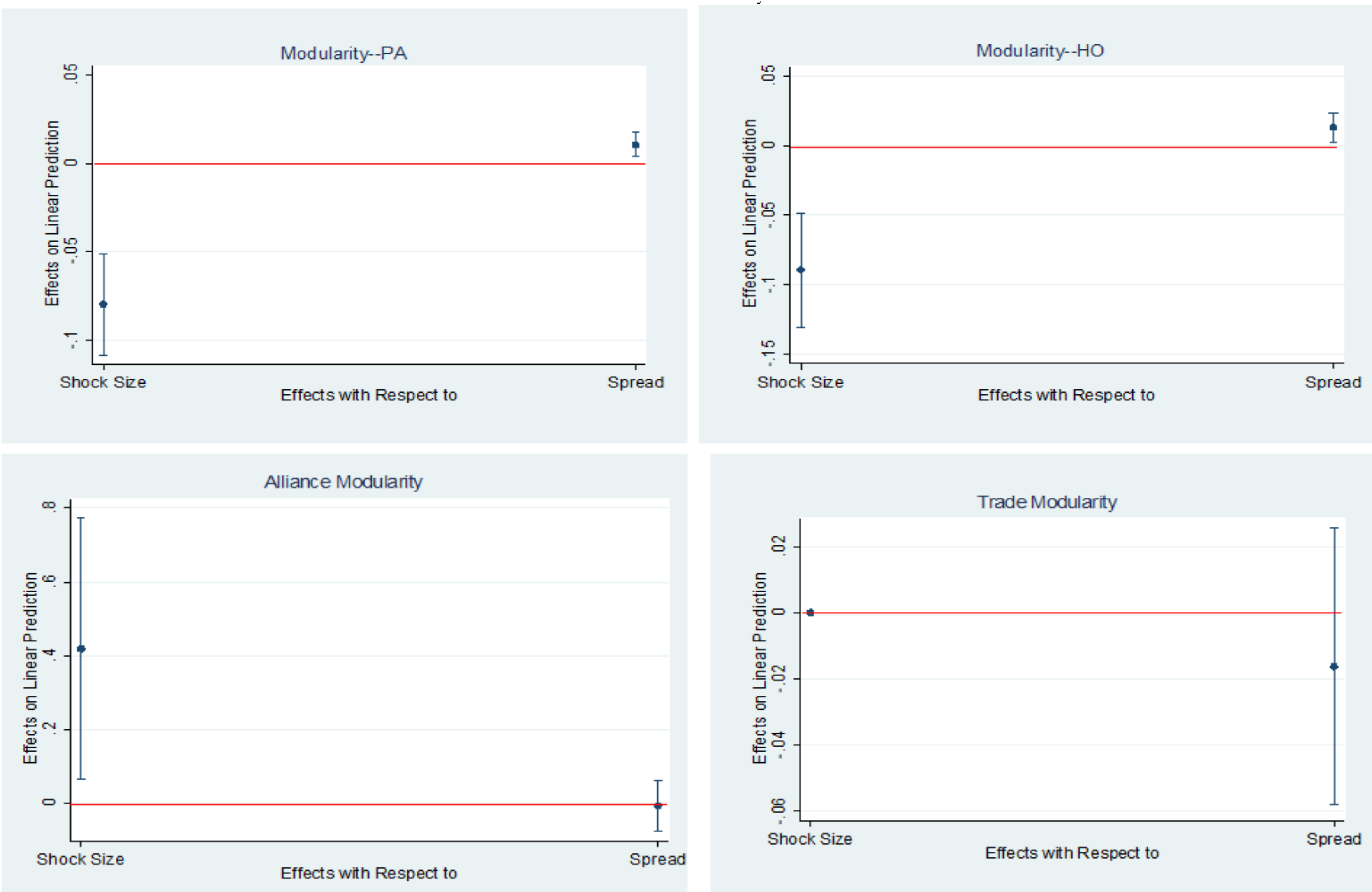
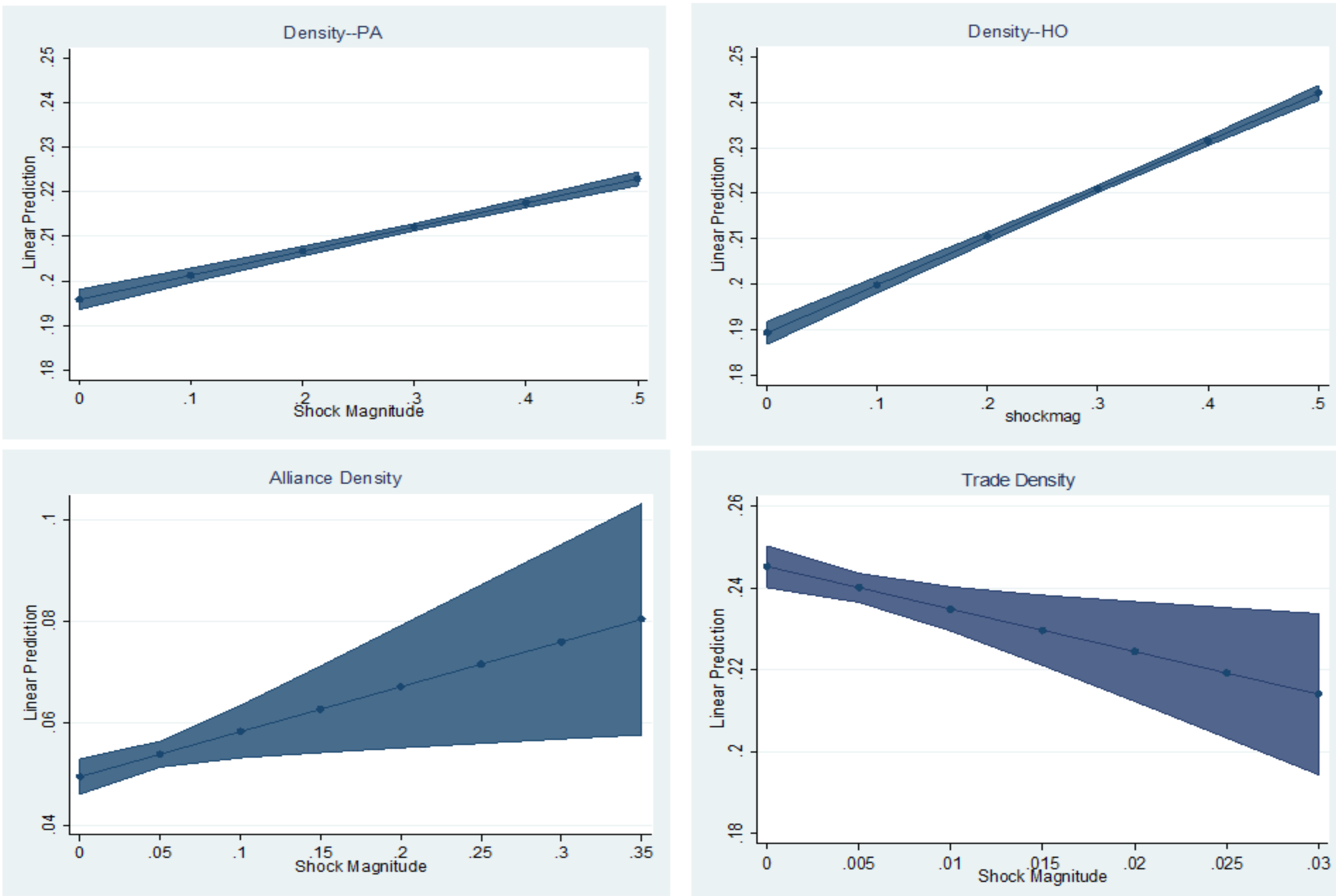
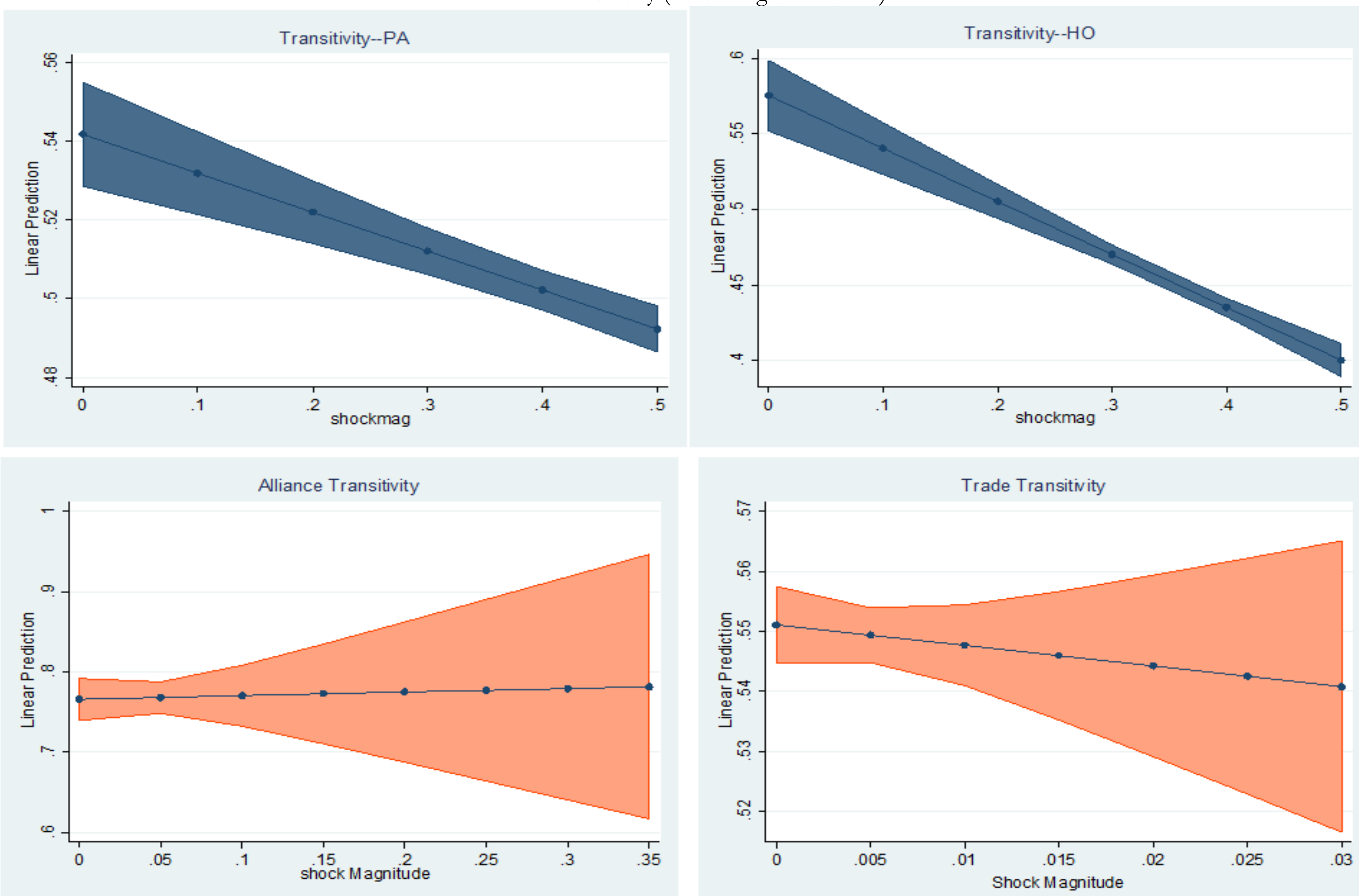


Figure 5: The Effects of Shocks on Network Characteristics
5.1. Density



5.2. Transitivity (Clustering Coefficient)



5.3. Average Path Length