Free Riding, Network Effects, and Burden Sharing in Defense Cooperation Networks

Brandon J. Kinne[a]* and Stephanie N. Kang[b]

[a,b]Department of Political Science, University of California, Davis, USA
*Corresponding author. Email: bkinne@ucdavis.edu

Abstract How do states distribute the burdens of collective defense? This paper develops a network theory of burden sharing. We focus on bilateral defense cooperation agreements (DCAs), which promote cooperation in a variety of defense, military, and security issue areas. Using a computational model, we show that DCA partners' defense spending depends on the network structure of their agreements. In bilateral terms, DCAs increase defense spending by committing states to defense activities and allowing partners to reciprocally punish free riding. However, as a state's local network of defense partnerships grows more densely connected, with many transitive "friend of a friend" relations, DCAs have the countervailing effect of reducing defense spending. The more deeply integrated states are in bilateral defense networks, the less they spend on defense. We distinguish two potential mechanisms behind this effect—one based on efficiency improvements, the other on free riding. An empirical analysis using multilevel inferential network models points more to efficiency than to free riding. Defense networks reduce defense spending, and they do so by allowing countries to produce security more efficiently.

Problems of burden sharing and defense cooperation have come to the fore of public debate. During his tenure in office, US president Donald Trump frequently took aim at NATO, singling out member states for "not paying their fair share"[1] and insisting that "the distribution of costs has to be changed."[2] Burden sharing encapsulates a fundamental collective-action problem—how best to divide the burden of common defense among partners—that extends across the realm of international security.

This paper develops and tests a network theory of burden sharing. Recent work on networks shows that the structure of international relations substantially influences state behavior.[3] Classic public-goods models of burden sharing—in which

1. "Trump Says NATO Countries' Burden-Sharing Improving, Wants More," Reuters, 2 April 2019.
2. "A Transcript of Donald Trump's Meeting with the Washington Post Editorial Board," *Washington Post*, 21 March 2016.
3. Chyzh 2016; Duque 2018; Kinne 2013, 2018; Maoz 2009; Murdie 2014; Ward, Siverson, and Cao 2007; Warren 2016.

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contributions or "spill-ins" from alliance partners affect individual defense effort[4]—implicitly acknowledge this network context but do not consider its implications. Empirical studies of burden sharing often focus on country-level determinants of defense spending, such as economic constraints or political ideology.[5] Much less is known about how states select defense partners, and how the resulting network structure of those partnerships influences burden sharing.

Our analysis focuses on defense partnerships established through bilateral defense cooperation agreements, or DCAs. These agreements have proliferated dramatically since the early 1990s and now play a central role in the global security environment.[6] By promoting a broad range of cooperative activities—intelligence sharing, arms trade, training and officer exchanges, peacekeeping operations, and joint military exercises, among others[7]—DCAs help countries modernize their militaries and pool resources against shared threats. Because these activities require defense outlays, DCAs naturally pose the question of whether formal defense commitments lead to increased defense effort.

Our network approach to burden sharing shows that defense agreements have divergent effects on defense spending. In strictly bilateral terms, DCAs enable detection and informal punishment of free riders. Contrary to the "large numbers" problem of public-goods models, defense spending increases as countries sign more DCAs. However, the network structure of defense agreements exercises a countervailing influence. As states form increasingly dense defense ties, characterized by friend-of-friend relations or "transitive triads" in their local networks of partners, defense agreements in fact reduce spending. The overall impact of defense cooperation on burden sharing thus depends on how defense relations are structured. We use an agent-based model (ABM) of network–behavior coevolution to develop the argument and derive hypotheses, and we test the hypotheses with inferential network models.

This analysis makes three contributions to our understanding of burden sharing. First, we show that forming defense partnerships and determining an appropriate level of defense effort are interdependent processes. Governments do not create defense agreements randomly but instead *select* those partners that best contribute to mutual defense.[8] At the same time, these partnerships determine the *influence* of agreements on burden sharing. Put differently, defense partnerships and individual defense effort coevolve over time, and the influence of those partnerships on burden sharing depends, in part, on how states select partners.

Second, we theoretically separate the bilateral influence and network influence of DCAs, and we empirically assess the independent impact of each. We find that although bilateral DCAs put upward pressure on defense expenditures, as those agreements congeal into dense local networks they instead reduce individual

4. Olson and Zeckhauser 1966.
5. Chowdhury 1991; Whitten and Williams 2011.
6. Kinne 2018.
7. Kinne 2020, 730.
8. Digiuseppe and Poast 2018.

defense effort. This network effect is wholly unapparent from a bilateral perspective. Post-estimation analysis further reveals that the DCA network is a more important determinant of defense spending than virtually all covariates, including regime type, alliance membership, and economic growth.

Finally, we identify two distinct mechanisms that connect network structure to reduced defense effort. On the one hand, dense local networks may promote convergence in defense policies, rendering defense cooperation less costly and more *efficient*. On the other hand, dense local networks may undermine reciprocity-based punishments and increase the publicness of defense goods, inviting *free riding*. Scholarship on burden sharing recognizes the importance of both mechanisms.[9] We incorporate these mechanisms into the ABM, derive testable hypotheses for each, and empirically determine which effect dominates. The results suggest that DCA networks reduce defense effort primarily by generating efficiencies, not by inducing free riding.

Overall, the network perspective shows both that particular structures of cooperation reduce defense effort, and that such reductions are not necessarily suboptimal. Rather, networks may allow states to produce security more efficiently. This finding means that individual contributions to burden sharing should be viewed from a broader network context, as instances of apparent free riding may in fact reflect network efficiencies. More generally, these findings underscore the importance of theorizing and empirically modeling international relations as a global network, where network structure influences behaviors in ways that are unobservable from standard dyadic perspectives.

Defense Cooperation and Burden Sharing

The literature on burden sharing typically focuses on formal alliances.[10] The economic theory of alliances, first articulated by Olson and Zeckhauser, is perhaps the most widely employed burden-sharing framework.[11] In this view, alliances produce pure public goods, such as deterrence or reduced militarized conflict. Because these goods are nonexcludable and nonrival, they create incentives for countries to free ride, or enjoy the security benefits of defense cooperation at little or no cost to themselves. Others argue that alliances generate "joint products"—not only pure public goods, but also private and impure public goods. Free riding declines, but does not altogether disappear, when the gains of defense cooperation are more commensurate with individual effort.[12]

While research on alliances has produced important insights on defense cooperation, we know little about burden sharing beyond alliances. Formal alliances exist

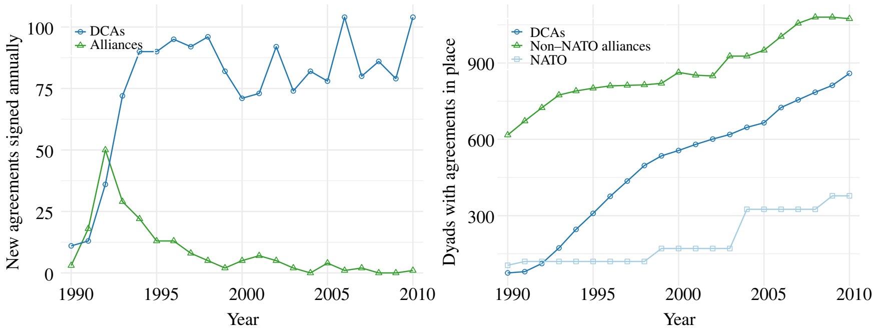
9. Olson and Zeckhauser 1966; Sandler and Hartley 2001.
10. E.g., Fuhrmann 2020; Oneal 1990; Sandler 1993.
11. Olson and Zeckhauser 1966.
12. Cornes and Sandler 1984.

primarily to deter conflict,[13] and they focus more on partner reliability in militarized confrontations than on routine cooperation.[14] DCAs, by contrast, involve no defensive, offensive, neutrality or other conflict-specific commitments, and they explicitly establish "institutional frameworks for routine defense cooperation."[15] DCAs encourage such day-to-day defense activities as military exercises, training and officer exchanges, arms trade, peacekeeping, research and development, and sharing of classified information, with a combined focus on interstate security issues and more nontraditional threats like terrorism, maritime security, and nonstate armed groups.

States continue to sign new DCAs at a high rate, and there are now nearly as many dyads with DCAs in place as there are dyads with alliances (Figure 1). These empirical trends, combined with the emphasis of DCAs on routine, substantive defense cooperation—which places an immediate expectation on states to contribute to joint security—present an opportunity to explore burden sharing beyond formal alliances. Further, the institutional features of DCAs mitigate common methodological problems. DCAs tend to be (1) similarly structured, prioritizing a common set of issue areas; (2) virtually always bilateral; and (3) lacking in institutionalized enforcement mechanisms.[16] These features hold constant the potential confounding influences of institutional design, issue-area variation, multilateral politics, and intergovernmental organizations.

Most importantly, existing research does not consider how endogenous aspects of defense cooperation affect burden sharing. The choice to sign defense agreements with particular partners is not independent of the subsequent influence of those agreements on defense behavior. Defense scholars typically treat partner selection as exogenous.[17] Yet, as Digiuseppe and Poast observe with regard to alliance formation, "defense pacts and military spending are co-determinous processes."[18] In networks, states strategically select partners to maximize their utility, and this selection process generates distinct network structures.[19] Scholars of international relations have shown that across issue areas—alliance formation, militarized conflict, status and reputation, trade and human rights, and even joint security production[20]—network structures influence behavior. Yet, despite the implicit network logic of free-riding arguments,[21] studies of burden sharing typically focus on exogenous factors like external threats, domestic politics, leader attributes, or financial constraints.[22] We

13. Benson 2012; A. Smith 1998.
14. Crescenzi et al. 2012; Leeds 2003; Mattes 2012. According to data from Leeds et al. 2002, less than 15 percent of alliances require peacetime contact between member states.
15. Kinne 2018, 803.
16. Kinne 2020.
17. Lai and Reiter 2000; Simon and Gartzke 1996.
18. Digiuseppe and Poast 2018, 997.
19. Kinne 2013.
20. E.g., Beardsley et al. 2020; Chyzh 2016; Cranmer, Desmarais, and Kirkland 2012; Duque 2018; Maoz 2009; Ward, Siverson, and Cao 2007.
21. Olson and Zeckhauser 1966.
22. E.g., DiGiuseppe 2015; Fuhrmann 2020; Nordhaus, Oneal, and Russett 2012; Whitten and Williams 2011.



Notes: Left panel shows number of new agreements signed per year. Right panel shows number of unique country-pairs (dyads) with agreements in place. Alliance data from Leeds et al. 2002. Nonaggression pacts excluded. DCA data from Kinne 2020.

FIGURE 1. *Trends in defense cooperation agreements (DCAs) and alliances, 1990–2010*

show that network structures matter both for the selection of defense partners and for the influence of partners on individual defense effort.

A Network Theory of Burden Sharing

In Olson's classic model, provision of public goods decreases as group size grows.[23] Large alliances thus encourage free riding.[24] This logic provides a baseline expectation for DCAs. As a focal state's number of DCA partners increases, its incentive to free ride on its partners' efforts increases, and its defense spending declines. This well-known "large numbers problem" relies on three assumptions: (1) there is a distinct group of actors, and the fraction of the group benefit for any given actor shrinks as the group grows; (2) states cannot easily implement the strategic interactions needed to encourage contributions; and (3) organization costs are high.[25]

These assumptions readily apply to multilateral agreements and formal organizations. But DCAs are not multilateral and do not create organizations.[26] Instead, DCAs are separable bilateral agreements, and they produce defense benefits that, *prima facie*, resemble club goods, shared among the members of the arrangement.[27] In practical terms, DCAs provide a way for states to align their defense policies

23. Olson 1965, 35.
24. Olson and Zeckhauser 1966, 268.
25. Kahler 1992, 683.
26. Thompson and Verdier 2014.
27. Buchanan 1965; Sandler 2013.

toward shared goals and interests.[28] This alignment may involve large-scale strategic issues, such as determining which global threats to prioritize and how to respond to those threats.[29] Or alignment may involve technical considerations like interoperability, logistics and supply, training standards, and information-sharing protocols, among others. When defense policies align, states prioritize similar types of threats and implement similar operational standards in addressing those threats.

Production of collective security goods requires not only that states align their policies but also that they make ongoing contributions to mutual defense. To modernize their militaries, for example, governments must invest in research and development, weapons procurement, training, and innovative military doctrines. Improving access to classified intelligence requires investments in signal and human intelligence-gathering capabilities (such as satellites and spies), as well as implementation of safeguard protocols at the organizational level. Any agreed-upon joint actions—military exercises, peacekeeping operations, counterterrorism operations—necessitate further operation-specific expenditures. Without mutual contributions, the benefits of defense cooperation are minimal.

As bilateral agreements, DCAs include an informal punishment mechanism.[30] If one partner falters in its obligations, the other withholds its own contribution, and the club good is not produced. The bilateral nature of DCAs enables tit-for-tat strategies that encourage individual defense effort.[31] Governments are acutely aware of this mechanism. Turkey's DCA with Indonesia, for example, explicitly defines cooperation as "activities based upon reciprocity."[32] Implementing reciprocity-based punishments is simply a matter of withholding cooperation in response to perceived lack of effort by partners. Such reciprocity gradually undermined a 1995 DCA between Indonesia and Australia, until the agreement was abrogated in 1999.[33] Less dramatically, reciprocal punishments leave agreements to languish, such that they fail to produce security goods. In strictly bilateral terms, contrary to the large-numbers problem, this potential for punitive reciprocity should encourage defense spending.

The Network Structure of Defense Cooperation

However, DCAs are not merely bilateral. They also comprise a larger network. A network consists of a set of agents, or "nodes," connected by a set of ties, or "edges." Network ties are interdependent; the formation, maintenance, and/or termination of one edge depends on edges elsewhere in the network. In addition to maintaining their ties, nodes engage in various unit-level behaviors, such as allocating

28. Abercrombie 2019; Loewen 2018.
29. Fazal and Poast 2019; Porter 2019.
30. Sandler 2013; Verdier 2008.
31. Keohane 1986; Sandler and Hartley 2001.
32. Agreement on Defense Industry Cooperation between the Government of the Republic of Indonesia and the Government of the Republic of Turkey, 29 June 2010, Article III.
33. "Indonesia Revokes Defense Pact with Australia," *Wall Street Journal*, 17 September 1999.

expenditures to defense, which may affect—or be affected by—edge formation. This network–behavior setup allows us to theorize the *selection* of defense partners and the *influence* of those partners on defense effort from within a single coevolutionary framework.

(a) Intransitive triad (b) Transitive triad

FIGURE 2. *Two types of triadic structures*

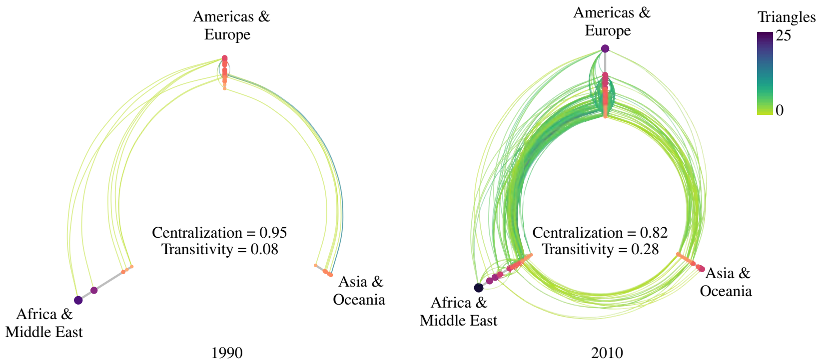
As the network evolves, distinctive structures emerge. These structures may generate higher-order effects that disrupt the straightforward logic of bilateral cooperation.[34] Accordingly, we separate the *bilateral* influence of DCAs from their *network* influence. We focus on one particular network structure, the transitive triad, also known as a triangle, wherein three nodes are mutually connected by three unique edges, as illustrated in Figure 2.[35] Triads are the building blocks of networks. They enable social arrangements—mediation, brokerage, coalitions—that are impossible with only two actors.[36] Triads are also essential to more complex network features, such as hierarchy, clustering, and modularity.[37] As the most elementary form of network structure, triads provide crucial insight into the effects of structure on behavior.

Analyzing the topology of the DCA network reveals that DCA ties have grown increasingly transitive, such that bilateral DCA partners often have mutual DCA ties to common third parties (Figure 3). At the same time, the network has grown denser and less "centralized," or less dominated by a small number of highly active nodes (such as major powers). The key question is how these structural features matter for burden sharing.

Selection and Influence at the Network Level

To understand how network structure influences defense effort, we merge network-analytic concepts with insights from the burden-sharing literature. We identify two specific mechanisms—one based on policy convergence and efficiencies, the other on free riding—that connect transitive triads to burden sharing.

34. Hollway and Koskinen 2016; Kinne and Bunte 2020; Maoz 2012.
35. Holland and Leinhardt 1971.
36. Simmel 1950.
37. Newman 2006; Newman and Girvan 2004.



Notes: Nodes are countries. Edges are DCAs. Node size and color correspond to defense expenditures as a percentage of GDP. Edge color indicates the number of triangles in which each edge is embedded. Centralization and transitivity are calculated at the global level.

FIGURE 3. *DCA network topology at two time points*

Efficiency concerns, or the quantity of security produced relative to spending, are central to burden sharing.[38] Research on alliances shows that certain defense policies —such as "sharing and standardization schemes" to ensure interoperability of weapons and forces[39]—can reduce defense outlays by promoting complementarity and mitigating risk.[40] Building on this insight, we focus on *network efficiencies*. A network efficiency exists when actors derive utility not only from their individual ties but also from the structure of those ties.[41] For transitive triads, network efficiency means that the aggregate utility generated by a triangle is greater than the sum of those ties' individual utilities. Put differently, states benefit from the joint defense products of each DCA in which they are members, *and* they benefit from the overall connectedness of their DCA partners. By this logic, the structure in Figure 2(b) generates more utility for a given focal node than does the structure in 2(a), even if its number of direct ties is identical in the two cases. Network efficiencies are similar to synergy effects.[42]

Transitive triads can generate efficiencies by facilitating convergence in the defense policies of states, thus reducing the costs of defense cooperation.[43] This argument prioritizes the role of DCAs in defense policy coordination and builds on the burden-sharing literature's emphasis on policy-driven sources of efficiency. As Pannier and Schmitt observe, "policy convergence is a prerequisite to effective

38. Sandler and Hartley 2001, 872.
39. Sandler and Forbes 1980, 428.
40. Compare Conybeare 1994, 415–17.
41. Jackson 2003; Jackson and Wolinsky 1996.
42. Cranmer, Desmarais, and Kirkland 2012.
43. Bennett 1991; Cao 2017; Drezner 2001; Greenhill 2010; Greenhill, Mosley, and Prakash 2009.

cooperation."[44] When governments share strategic goals, they can more readily identify and act on mutual threats. In technical areas, by coordinating policies on interoperability, training, logistics, and other standards, governments can subsequently engage in joint exercises, counterterrorism and peacekeeping operations, arms trade, and investment in research and development. For example, policies that improve interoperability—on such issues as ammunition caliber, aerial refueling technology, and software protocols, for example—allow defense partners to adopt exchangeable force units and hardware, increase compatibility in communications technology, and standardize data exchanges.[45]

Defense policy adjustments are costly and must contend with budgets, bureaucracies, technological limitations, and other barriers.[46] The wider the policy gap between prospective partners, the greater the costs of adjustment.[47] In a transitive triad, focal node *i*'s partners *j* and *k* are also aligned with one another by virtue of their direct tie, *jk*. Thus any policy adjustments *i* makes with regard to one partner are extensible, in part, to others. This effect is similar to regulatory convergence, where governments adopt a modal policy in lieu of multiple, potentially contradictory regulations.[48] On sharing of classified information, for example, the US maintains different standards with South Korea than it does with Japan, largely due to an absence of direct Japan–Korea standardization. When attempting to cooperate on issues of mutual interest, such as the North Korean threat, this patchwork arrangement "only covers about half the necessary information and creates significant lag in the information flow."[49] Standardization between Japan and South Korea would allow the US to implement a common intelligence-sharing policy with regard to both states. More generally, transitive triads reduce the need for discrepant standards and allow states to coordinate policies at lower cost.

As transitive triads persist, they push defense policies further into alignment via third-party influences. When two states align their policies with a common third party, they indirectly align those same policies with one another. This convergence, in turn, reduces the operational costs of defense activities. For example, the defense policies that Japan and Australia individually adopted in their respective relations with the US ultimately lowered barriers to direct Japan–Australia cooperation on arms procurement, joint ballistic missile defense, intelligence sharing, and force complementarity.[50] Similarly, the post-World War II hub-and-spoke system of bilateral ties in East Asia, defined by policy coordination with the US, facilitated coordination between the spokes themselves, yielding a "web of security relations" and frequent

44. Pannier and Schmitt 2014, 271.
45. Hura et al. 2000.
46. Bellais and Guichard 2006; R. Smith 1995; Whitten and Williams 2011.
47. Drezner 2005, 846.
48. Lazer 2001.
49. Wicker 2016, 6.
50. Wilkins 2015, 102–03.

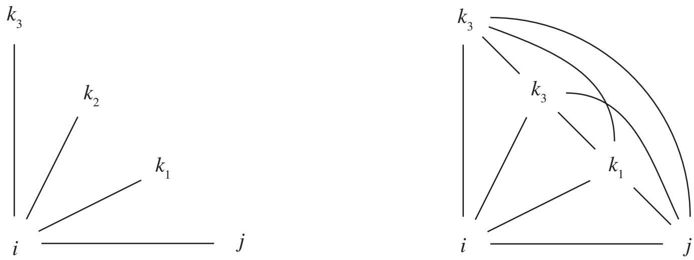
joint military activities.[51] This indirect convergence effect mirrors a general homophily effect, observed in many social networks, where third-party ties increase belief similarity.[52] Such third-party influences promote efficiency by lowering policy barriers to defense activities.

Finally, transitive triads reduce the operational costs of trilateral or larger plurilateral actions, such as peacekeeping, military exercises, and counterterror operations. Effective trilateralism requires extensive "spoke-to-spoke" interaction, where each leg of the triangle effectively coordinates with the others.[53] From *i*'s perspective, the more closely aligned *j* and *k* are, the more easily all three states can leverage their respective bilateral ties for trilateral purposes. For example, Turkey has long encouraged greater policy coordination between Azerbaijan and Georgia—its two key defense partners in the Caucasus—in the hopes of promoting trilateral activities, improving regional security, and avoiding the expense of holding separate bilateral exercises, trainings, and exchanges.[54] This policy alignment within transitive triads lowers operational costs in similar fashion to "minilateral" strategies.[55]

The allure of reduced adjustment and operational costs directly affects partner selection. Countries have an incentive to *select* partners in a way that yields transitive triads and captures network efficiencies. As they do so, *dense local networks* emerge, where a given node's defense partners are also partnered among themselves (Figure 4). This structure maximizes triangle-based efficiencies. While an accumulation of bilateral ties—as in a sparse local network—increases a given node's defense obligations, a dense local network lowers the costs of those obligations. *Ceteris paribus*, the lower the costs of security production, the weaker the demand for defense outlays.[56] Precisely this outcome motivates states to form triangles in the first place. In terms of *influence*, then, the focal node's defense spending should decrease as the density of its local network increases.

Importantly, efficiency-driven reductions in defense effort are the result of lowered costs, not free riding. However, dense local networks may also incentivize free riding, in two ways. First, as with network effects more generally,[57] the utility generated by efficiencies increases with the number of participants. As states converge in their security strategies, a growing number of partners stands to benefit from the actions of a few vigilant actors. Policy convergence increases the odds that the security-minded efforts of some states will address threats of importance to others, thus increasing the publicness of defense goods. By demarcating groups of like-minded states—defense partners in dense local networks—and expanding the range of

51. Blair and Hanley 2001, 9–11.
52. Asikainen et al. 2020; Kossinets and Watts 2009. This effect has also been observed in socio-economic networks like environmental standards (Loconto 2017) and trade regulations (Corning, 2020).
53. Satake 2011, 19.
54. Cecire 2016.
55. Wuthnow 2019, 136–37.
56. Sandler and Hartley 2001, 872.
57. Katz and Shapiro 1994.



(a) Sparse local network

(b) Dense local network

FIGURE 4. *Sparse versus dense local networks*

beneficiaries, network efficiencies resurrect a key assumption behind the large-numbers problem: that a distinct group exists, and larger groups reduce the fractional benefit for any given actor.[58]

Second, dense local networks may endanger the reciprocity mechanism that deters free riding at the bilateral level. As political economists have long argued[59]—and as Farrell and Newman show with regard to economic networks and security issues[60]—policy interdependence reduces flexibility. In a dense local network, *j*'s attempts to punish a free-riding *i* are more likely to negatively impact *j*'s other partners—who expect to benefit from production of defense goods—regardless of whether those third parties engage in free riding themselves. If dense local networks indeed reduce states' ability to deter free riding via strategic interactions, they effectively reinstate the additional two assumptions behind the large-numbers problem—that is, states lack strategic mechanisms to encourage contributions, and they face organizational costs.[61] Opportunistic states, recognizing the limited ability of their partners to inflict punishments, can more easily free ride on those partners' efforts. Notably, free riding in this case arises not from multilateral treaties or international organizations but from network structure.

Both efficiency and free riding reduce defense spending, but for starkly different reasons. Separating these mechanisms is necessary to illuminate the overall security benefits of defense cooperation. A key distinction is that efficiencies are a general effect of network structure as such,[62] while free riding is conditional on the defense effort of one's partners.[63] That is, efficiencies emerge when defense partnerships coalesce into transitive triads. By contrast, the incentive to free ride on the efforts of

58. Kahler 1992, 683.
59. Rodrik 2000, 182–83.
60. Farrell and Newman 2019.
61. Kahler 1992, 683.
62. Jackson and Wolinsky 1996.
63. Olson and Zeckhauser 1966, 268.

other states depends on the effort expended by those states. We exploit this distinction to separate the effects of network efficiencies from triangle-induced free riding.

A Computational Model of Network–Behavior Coevolution

To derive testable hypotheses, we must (1) explicitly model interdependence between selection and influence; (2) separate the bilateral and network influences of DCAs; and (3) distinguish the effects of network efficiencies from those of free riding. Because network relations and individual behaviors are mutually endogenous, models that rely on analytic solutions, such as game-theoretic and decision-theoretic models, are generally not feasible. Instead, we build an ABM using a network–behavior coevolution approach, which is designed to assess how network relations and individual behaviors mutually influence one another.[64] Similar ABMs have been used to study selection–influence dynamics across a range of networks and behaviors, including the international system.[65] A methodological benefit of this approach is that it is readily extensible to empirical analysis, as discussed later. This subsection explains the key elements of the ABM. The online supplement gives a thorough presentation.

Consider a finite set of agents, $N = \{1, \ldots, n\}$, with ties $g \in \{0, 1\}$, in an $n \times n$ matrix, representing bilateral DCAs. The $n \times 1$ matrix $r \in \{1, \ldots, M\}$ defines an individual behavior, scaled across M ordinal categories, representing defense effort. Agents adjust their ties or behaviors when given an opportunity to do so according to separate rate functions, such that g and r coevolve in continuous time. A focal agent i may create a new network tie, terminate an existing one, or make no change at all. Let g^+ denote the network that exists after i has been given an opportunity to adjust its ties. Similarly, let r^+ denote the matrix of behaviors that results from i having an opportunity to change its behavior. When agents adjust their ties or behavior, they maximize their utility with respect to two objective functions: $f_i^{\text{net}}(g, g^+, r)$ for the network and $f_i^{\text{beh}}(g, r, r^+)$ for behavior.

The network choice probabilities for i are defined as

$$P(g^+) = \frac{\exp\left(f_i^{\text{net}}(g, g^+, r)\right)}{\sum_{k=1}^{n} \exp\left(f_i^{\text{net}}(g, g^{+k}, r)\right)} \qquad (1)$$

64. See Snijders 2001; Steglich, Snijders, and Pearson 2010. While there is a growing literature on network games (Jackson and Zenou 2015), the bulk of this work addresses fixed networks, with network structure as an exogenous, static influence (Bramoullé and Kranton 2016). The few existing game-theoretic models of network–behavior coevolution are exploratory and require highly restrictive assumptions about network formation to arrive at closed-form solutions. For example, Canen, Jackson, and Trebbi 2022 assume that network ties form according to a "random matching protocol," while Badev 2021 assumes a process of chance encounters among a predetermined subset of nodes. Further, network games predict a large number of equilibria (Galeotti et al. 2010, 219), many of them trivial or unrealistic, and are not amenable to empirical analysis (Badev 2021, 1182).

65. Bianchi, Flache, and Squazzoni 2020; Finn et al. 2019; Lehmann, Rolfsen, and Clark 2015; Stadtfeld, Takács, and Vörös 2020; Zhang et al. 2015.

where the sum in the denominator refers to all possible g^{+k} states of the network, or the options available to i for toggling its network ties.[66] Similarly, the choice probabilities for behavior change are defined as

$$P(r^+) = \frac{\exp(f_i^{\text{beh}}(g, r, r^+))}{\sum_{k=1}^{M} \exp(f_i^{\text{beh}}(g, r, r^{+k}))} \tag{2}$$

where the sum in the denominator refers to possible r^{+k} levels of the behavior.

The ABM implements these objective functions as linear combinations of effects:

$$f_i^{\text{net}}(g, g^+, r) = \sum_h \beta_h^{\text{net}} s_h^{\text{net}}(i, g, g^+, r) \tag{3}$$

$$f_i^{\text{beh}}(g, r, r^+) = \sum_h \beta_h^{\text{beh}} s_h^{\text{beh}}(i, g, r, r^+), \tag{4}$$

where the statistics s_h must be specified on the basis of theory and may include endogenous features of the network g, various aspects of behavior r, or exogenous covariates. The β_h parameters are weights that determine the extent to which agents attempt to achieve a network–behavioral state that yields large values for the corresponding s_h statistics. The ABM captures network–behavior coevolution by including behavior terms in the network equation and network terms in the behavior equation.

The ABM defines a micro-level, actor-oriented process,[67] which approximates the decision-theoretic approaches common in the study of burden sharing.[68] The outcomes of interest are macro-level features of the network and behavior, which are not themselves explicitly modeled but are emergent properties.[69] We derive hypotheses by observing how the ABM specification affects these macro-level outcomes. The key outcome in this case is mean defense effort. The ABM outcomes are statistical approximations of stable equilibria in which agents cannot further improve their utility.[70] See the online supplement for equilibrium analysis.

We calibrate the ABM using observed empirical data on the DCA network and defense spending for the year 2000.[71] The initial g matrix is the observed DCA network, where $g_{ij} = 1$ indicates a DCA in force. The initial r matrix is an eleven-point scale ($M = 11$) of country-level defense effort, derived from defense spending as a percentage of GDP. By assuming that individual behavior takes on ordinal

66. Note that because DCA networks are nondirected, target j of i's network tie must confirm the tie in order for it to be created, based on a choice probability similar to that in equation (1). See the online supplement.

67. Snijders and Steglich 2015.

68. Butts 2017, 48.

69. Pumpuni-Lenss, Blackburn, and Garstenauer 2017.

70. De Marchi and Page 2014, 10–11.

71. The data sources are the same as those used in the empirical analysis. The choice of year is inconsequential.

values, we can represent network–behavior coevolution in a common statistical framework—specifically, a continuous-time Markov chain with a discrete outcome space.[72] A continuous behavior metric would entail a virtually infinite number of choices (see equation (2)), which is computationally infeasible. In network–behavior models, discretization is widely used and well established.[73] We discretize defense-spending data at absolute 1 percent increments from zero to 10 percent, with a residual category for spending above 10 percent; that is, we specify cut points at $[0, 0.01, \ldots, 0.1, 1]$.[74]

DCA Degree and Defense Spending

We first examine the $f_i^{\text{beh}}(g, r, r^+)$ behavior function in isolation. We specify the standard public-goods model described by Sandler and Hartley, where optimal defense effort for country i is a function of the price of defense goods, national income, level of threat, and spill-ins from defense partners.[75] When the relationship between spill-ins and defense effort is the focus, the additional terms in the model can be held constant, which allows derivation of reaction functions that indicate i's optimal response to the efforts of its partner j.[76] We model this response as

$$f_i^{\text{beh}}(g, r, r^+) = \alpha^{\text{beh}} r_i + \pi c_i + \gamma d_i, \tag{5}$$

where $\{\alpha^{\text{beh}}, \pi, \gamma\}$ are the β_h^{beh} parameters of equation (4), given unique designations for clarity. r_i is agent i's current level of defense effort. c_i is the ith observation of an $n \times 1$ random variable with an exponential distribution that represents exogenous, unit-specific demands for defense spending, such as variations in national income and/or exposure to security threats. d_i is i's number of partners in the DCA network, or "nodal degree," which reflects anticipated defense contributions from one's partners and thus corresponds to spill-in in the public-goods framework.[77] Table 1 lists all the component variables of the ABM, with formal definitions. See the online supplement for parameter profiles.

The γ parameter determines the effect of i's DCAs on its utility. The claim that free riding increases with group size assumes that γ is negative.[78] As defense partners increase in number, the incentive to spend on defense declines. Accordingly, we first set γ at incrementally decreasing values from zero. Because public-goods models do not consider network structure, at this point all parameters in the network equation are zero; that is, states select DCA partners at random.[79] We then simulate the coevolution of the DCA network and defense spending. Figure 5(a) illustrates

72. Niezink, Snijders, and van Duijn 2019, 296.
73. Niezink 2018, chapter 6.
74. Compare Ripley et al. 2021, 26.
75. Sandler and Hartley 2001, 873.
76. Sandler 1993, 453.
77. Conybeare, Murdoch, and Sandler 1994.
78. Olson 1965, 35.
79. Snijders 2001, 373.

equilibrium defense spending behavior as γ decreases. These equilibria mirror the familiar response curve of a decision-theoretic public-goods model.[80] The greater the anticipated spill-ins from defense partnerships, the less effort i expends on defense.

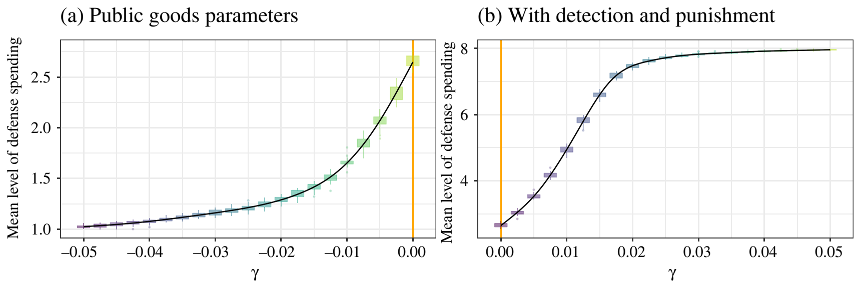
TABLE 1. *Summary of terms in the agent-based model*

Variable	*Parameter*	*Name*	*Definition*	*Description*
Defense spending equation				
r_i	α^{beh}	CONSTANT	r_i	Baseline defense spending behavior, or cost of defense effort
d_i	γ	DCA DEGREE	$r_i \sum_j^n g_{ij}$	Effect of bilateral DCAs on i's defense effort
q_i	ψ	DCA DENSE TRIADS	$r_i \sum_{j,k}^n g_{ij}g_{ik}g_{jk}$	Effect of DCA triangles on i's defense effort
z_i	η	DCA TRIADS EFFORT	$q_i r_i \sum_j^n g_{ij} r_j$	Effect of DCA triangles conditional on partners' defense effort
c_i	π	Monadic covariate	$r_i c_i$	Exogenous influences at the country level
DCA network equation				
$g_{i\bullet}$	α^{net}	DENSITY	$\sum_j^n g_{ij}$	Baseline tendency to form ties, or cost of DCAs
a_{ij}	τ	TOTAL DEGREE	$\sum_j^n g_{ij}(g_{j\bullet} + g_{i\bullet})$	Selection of partners based on total number of DCAs signed
b_{ij}	δ	TRANSITIVE TRIADS	$\sum_{j<k}^n g_{ij}g_{ik}g_{jk}$	Selection of partners based on closure of triangles
r_j	ζ	DEFENSE SPENDING$_j$	$\sum_j^n g_{ij} r_j$	Selection of high-spending partners
c_j	ϕ	Monadic covariate	$\sum_j^n g_{ij} c_j$	Exogenous country-level influences on partner selection
w_{ij}	ξ	Dyadic covariate	$\sum_j^n g_{ij} w_{ij}$	Exogenous country-pair influences on partner selection

By contrast, if bilateral agreements enable detection and punishment, then i cannot accrue the benefits of defense partnerships without making contributions. In this case, γ is positive, reflecting the utility i derives from spending on defense and ensuring continued cooperation from its partners. Figure 5(b) illustrates equilibrium defense spending as γ increases from zero. Contrary to the expectations of free-riding models, increases in γ sharply increase defense effort—despite the pressure of exogenous influences and the nonzero costs of defense. Two clarifications are in order. First, because γ parameterizes the relationship between nodal degree and individual behavior, the effect illustrated in Figure 5 depends not only on γ but also on each agent's respective nodal degree. That is, as a country's number of ties increases, so does the impact of γ on defense effort. Second, because this result is agnostic about network structure and the underlying process of network formation, it is strictly limited to the bilateral effects of DCAs. Overall, under the assumption that bilateralism facilitates reciprocal punishments, and as a counter to public-goods expectations, the model yields the following testable hypothesis:

> *H1: As a state's number of DCA partners increases, its defense spending increases.*

80. Sandler 1993, 455.



Notes: Based on 25 simulations of network–behavior coevolution for each $\gamma \in \{-0.05, \ldots, 0\}$ (left) and $\gamma \in \{0, \ldots, 0.05\}$ (right); $\rho = 200$. Box-and-whisker plots show distribution of defense spending behavior in each set of simulations. Black line is a loess curve across all simulations. Network partner selection is random.

FIGURE 5. *Equilibrium outcomes in the network–behavior agent-based model*

Influence of Transitive Triads

To incorporate the influence of network structure on defense spending, we must first specify the components of the network objective function, $f_i^{\text{net}}(g, g^+, r)$. Drawing on empirical work on DCA networks,[81] we specify

$$f_i^{\text{net}}(g, g^+, r) = \alpha^{\text{net}} g_{i\bullet} + \phi c_j + \xi w_{ij} + \zeta r_j + \tau a_{ij} + \delta b_{ij} \tag{6}$$

where $\{\alpha^{\text{net}}, \phi, \xi, \zeta, \tau, \delta\}$ are the β_h^{net} parameters of equation (3). The $\alpha^{\text{net}} g_{i\bullet}$ term models i's baseline tendency to form ties. As in equation (5), c_j is an $n \times 1$ random variable, which in this case reflects exogenous monadic attributes of j that influence partner selection. w_{ij} is a random variable in the form of an $n \times n$ matrix to account for exogenous dyadic influences. The ζr_j term models the tendency for i to select DCA partners that spend highly on defense. The endogenous term τa_{ij} accounts for the tendency of high-degree nodes to sign DCAs with other high-degree nodes.[82]

The final term, δb_{ij}, is the most critical. b_{ij} is the sum of triangles in i's network ties. The parameter δ determines the utility i derives from selecting defense partners in a way that yields triangles. If δ is positive, agents prefer to form dense local networks; if negative, agents prefer intransitive triads and sparse local networks. We set δ at a positive value to reflect the attraction of network efficiencies, consistent with existing empirical work.[83]

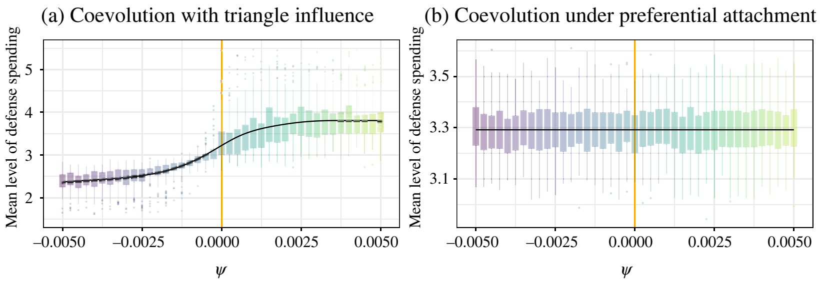
With equation (6) in place, we update equation (5) to include network structure:

$$f_i^{\text{beh}}(g, r, r^+) = \alpha^{\text{beh}} r_i + \pi c_i + \gamma d_i + \psi q_i \tag{7}$$

81. Beardsley et al. 2020; Kinne 2018; Kinne and Bunte 2020; Winecoff 2020.
82. Kinne 2018.
83. Kinne 2018; Kinne and Bunte 2020.

where q_i is a count of triangles in i's local network. The ψ parameter determines the additional utility that triangles generate for i. If triangles are irrelevant, then $\psi = 0$. If triangles generate network efficiencies, then ψ is negative.

The ABM uses both equations (6) and (7) to simulate the coevolution of the DCA network and defense spending. We vary ψ from negative to positive values while holding γ at a constant positive value, consistent with H1. This specification captures the countervailing effect of network structure even as, in purely bilateral terms, DCAs exert consistent upward pressure on defense effort. Figure 6(a) illustrates equilibrium defense-spending behavior. Positive values of ψ—which might obtain if, say, dense local networks improve detection and punishment—generate small increases in defense spending. By contrast, negative values of ψ result in correspondingly larger reductions in defense effort, consistent with the influence of network efficiencies. This result obtains even though the positive *bilateral* effect of DCAs, reflected in γ, remains unchanged.



Notes: Based on 100 simulations of network–behavior coevolution for each $\psi \in \{-0.005, \ldots, 0.005\}$. $\rho = 100$. Box-and-whisker plots show distribution of defense-spending behavior in each set of simulations. Black line is a loess curve across all simulations. *Left* $\delta := 0.5$. *Right* $\delta := -0.75$.

FIGURE 6. *Agent-based model with coevolution and dense local networks*

Network–behavior coevolution plays an essential role in generating these outcomes. We thus far have assumed a network formation process in which agents prioritize transitive triads ($\delta > 0$). Consider an alternative network formation process, known as "preferential attachment,"[84] where agents prefer ties to high-degree nodes and avoid transitive closure ($\delta < 0$). This process yields a hub-and-spoke topology, consistent with theories that emphasize hierarchy in the international system[85] and the primacy of great power politics.[86]

We simulated the ABM using this alternative parameter profile for network formation (equation (6)) while keeping the behavior profile (equation (7)) unchanged.[87]

84. Barabási and Albert 1999.
85. Jung and Lake 2011; Lake 2009.
86. Maoz 2012; Mearsheimer 2001.
87. Note that in this model the quantity a_{ij} in the τa_{ij} term is defined solely in terms of target j's nodal degree, which better represents the process of preferential attachment. See Barabási and Albert 1999.

This model generates sharply divergent outcomes, illustrated in Figure 6(b). Transitive triads have no discernible effect on defense spending, even though the parameters for equation (7) are identical to those used to produce the results in Figure 6(a). When states have little incentive to form triangles, then the influence of triangles on spending declines to trivial levels, *even if, in principle, triangles should reduce defense effort*. These results reinforce the crucial insight that network formation and individual behavior are interdependent processes. If we ignore the strategic motivations behind agents' selection of partners, or if we misunderstand those motivations, we may reach wildly divergent expectations about the influence of network ties on behavior. The model yields the following hypothesis:

> *H2: As the number of triangles in a state's local DCA network increases, its defense effort decreases.*

While these results are consistent with an efficiency mechanism, they may also be driven by free riding. To separate these mechanisms, we capitalize on the distinction noted earlier. Efficiencies are a general feature of network structure, not conditional on nodal attributes.[88] By contrast, the free-riding incentive depends on spill-ins from the efforts of one's defense partners.[89] Bilateralism mitigates free riding by enabling reciprocal punishments. Yet, as dense local networks undermine the ability of states to impose punishments, the free-riding incentive reemerges—specifically in the context of a dense local network, where an opportunistic agent can reap the gains of its triangle partners' efforts while strategically avoiding punishments.

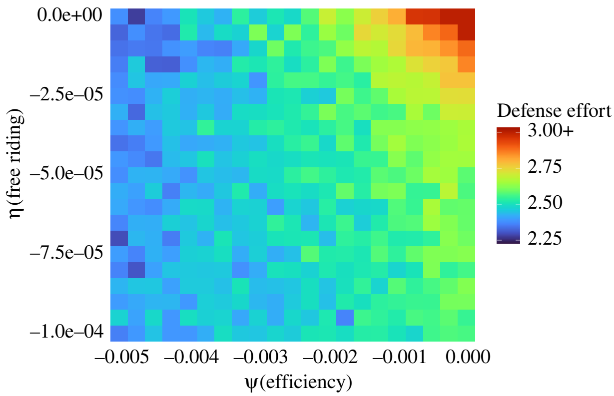
We model i's responsiveness to spill-ins from its triangle partners as

$$f_i^{\mathrm{beh}}(g, r, r^+) = \alpha^{\mathrm{beh}} r_i + \pi c_i + \gamma d_i + \psi q_i + \eta z_i, \tag{8}$$

where z_i measures triangles as a function of the defense effort of i's partners, and the parameter η determines the strength of the free-riding incentive, or i's prospects for evading bilateral punishments. Considering η alongside ψ separates the general effect of network efficiencies from the conditional effect of free riding.

Figure 7 illustrates the plausible parameter space for η and ψ as each decreases from zero. Free riding and efficiency are independently capable of reducing defense effort. That is, even if we altogether eliminate free riding ($\eta = 0$), triangles still push defense effort downward, regardless of partners' defense efforts, via the general influence of network efficiencies ($\psi < 0$). Conversely, if we assume that triangles as such generate no utility ($\psi = 0$) but we allow dense local networks to undermine reciprocity ($\eta < 0$), an opportunistic agent will reduce its defense effort so long as it obtains spill-ins from its local network

88. Jackson and Wolinsky 1996.
89. Sandler 1993, 451.



Notes: Cells indicate mean defense spending at specified ψ and η values, based on twenty-five simulations of network–behavior coevolution for each cell. $\rho = 100$. Specified ranges include parameter floor values; further decreasing ψ or η has no effect.

FIGURE 7. *Effect of efficiency and free riding on defense effort*

partners. These results cleanly separate the causal mechanisms and yield two testable hypotheses:

> *H3 (Efficiency)*: *Triangles reduce a state's defense effort regardless of the effort of its partners* $(\psi < 0, \eta = 0)$.

> *H4 (Free riding): Triangles reduce a state's defense effort only as the effort of its partners increases* $(\psi = 0, \eta < 0)$.

Overall, the ABM provides insights that, to our knowledge, have not been considered in the burden-sharing literature. First, the anticipated effect of defense agreements on defense effort depends on critical assumptions about whether an accumulation of bilateral DCAs raises the same large-*N* problems that plague collective action in multilateral and organizational frameworks. Second, states engage in a strategic selection–influence dynamic when joining defense agreements, and this dynamic generates distinctive network structures. Third, the network structures that emerge from strategic partner selection influence defense effort in ways that are not apparent from bilateral relations. Finally, these network influences may involve either free riding or efficiency, and these competing mechanisms carry distinct empirical implications.

Research Design and Data

The complexities of the ABM—simultaneous equations across levels of analysis, endogenous influences within the network, and selection–influence dynamics—are intractable in traditional regression-based empirical models. To our knowledge, the only established empirical model capable of modeling such features of network–behavior coevolution is the stochastic actor-oriented model (SAOM).[90] Fortunately, the network–behavior architecture of the ABM also underlies the SAOM, and moving from the ABM to empirical analysis is straightforward. The SAOM implements a simulated method-of-moments estimator, which uses network–behavior simulations to calculate expected values of included model statistics, compare those expected values to observed values, and derive parameter estimates. In this sense, the SAOM validates the ABM against real-world data.[91] In empirical studies of international relations, SAOMs have been used to model single networks over time,[92] network–behavior coevolution,[93] and dynamics of multiplex networks.[94]

We first update the objective functions to incorporate longitudinal empirical network–behavior data. Let **g** be a $1 \ldots T$ stack of symmetric, binary $n \times n$ matrices, where T is the number of years of data. As in the ABM, $g_{ij,t} = 1$ indicates that a DCA is in force between i and j in year t. Let **r** be a $1 \ldots T$ stack of $n \times 1$ matrices. Again mirroring the ABM, each $r_{i,t}$ entry of **r** takes on some ordinal integer value, where larger values indicate greater defense effort.

The empirical implementation of the network objective function in equation (3) can be written as

$$f_i^{\mathbf{g}}(\mathbf{g}, \mathbf{r}) = \sum_h \beta_h^{\mathbf{g}} s_{ih}^{\mathbf{g}}(\mathbf{g}, \mathbf{r}) \tag{9}$$

and the behavior objective function in equation (4) can be written as

$$f_i^{\mathbf{r}}(\mathbf{g}, \mathbf{r}) = \sum_h \beta_h^{\mathbf{r}} s_{ih}^{\mathbf{r}}(\mathbf{g}, \mathbf{r}) \tag{10}$$

To ensure that the empirical model aligns with the ABM, we use the same network terms in the SAOM as in the ABM (summarized in Table 1). For clarity, in the SAOM we refer to these terms by their full names. Equation (9) thus includes DENSITY, TOTAL DEGREE, TRANSITIVE TRIADS, and DEFENSE SPENDING$_j$, all of which are calculated on empirical DCA data. Similarly, equation (10) includes CONSTANT,[95] DCA DEGREE, DCA DENSE TRIADS, and DCA TRIADS EFFORT. We incorporate the exogenous covariates of the ABM, c_i, c_j, and w_{ij}, using multiple monadic and dyadic controls, as discussed later.

The SAOM uses empirical data to calculate observed values for each of the $s_{ih}^{\mathbf{g}}$ and $s_{ih}^{\mathbf{r}}$ statistics in the respective network and behavior objective functions. To obtain expected values for these statistics, the model simulates network–behavior

90. Snijders 2001; Steglich, Snijders, and Pearson 2010.
91. Snijders and Steglich 2015.
92. Kinne 2013, 2014; Manger, Pickup, and Snijders 2012; Warren 2010.
93. Chyzh 2016; Elkink and Grund 2022; Kinne 2016.
94. Hollway and Koskinen 2016; Htwe, Lim, and Kakinaka 2020; Kinne and Bunte 2020; Milewicz et al. 2018; Warren 2016.
95. We also include the square of *Constant* in case of nonlinearities.

coevolution using the same choice probabilities as in the ABM, where states adjust ties to maximize the function in equation (9) and adjust defense spending to maximize the function in equation (10). Unlike the ABM, these simulations are fully constrained by the observed data, and the parameter values are estimated rather than determined. A Robbins-Monro Markov-chain Monte Carlo algorithm searches the parameter space and locates vectors of parameter estimates, $\hat{\beta}_h^{\mathbf{g}}$ and $\hat{\beta}_h^{\mathbf{r}}$, where the expected values of the model statistics, calculated on the simulations, are equal to the observed values. Standard errors are derived using the delta method. Null hypotheses are tested with a standard t-statistic, $t_h = \frac{\hat{\beta}_h}{\text{s.e.}(\hat{\beta}_h)}$. See the online supplement for an extensive formal treatment.

We build the DCA network using Kinne's Defense Cooperation Agreement Dataset.[96] Our analysis employs the "general" category of DCAs, which includes only agreements that institutionalize the full range of countries' defense cooperative activities, including mutual consultation, training, joint exercises, intelligence sharing, research and development, and arms trade, among others. We obtain similar results if we also include "sector" DCAs (see the online supplement).

We measure country-level defense effort as defense expenditures divided by GDP.[97] We discretize this metric into eleven categories of defense effort, identical to the ABM. The online supplement explores discretization in greater depth and shows that the results are robust to numerous alternative approaches, such as increasing or decreasing the number of ordinal categories, taking log transformations, and using alternative metrics of defense effort. Data on expenditures come from the Correlates of War national military indicators data set.[98] GDP data are from the Penn World Table.[99]

In the network equation of the ABM, the terms w_{ij} and c_j reflect exogenous dyadic and monadic influences, respectively. To operationalize these terms, we draw on recent work on DCA networks, which shows that exogenous demand for DCAs is determined largely by geography, shared economic and political interests, membership in formal alliances, and economic resources.[100] We thus include the following controls:

- DISTANCE: the log-transformed geographic distance between i and j's capital cities.[101]
- ALLIANCE (NON-NATO): a dummy variable that equals 1 if i and j share membership in any alliance other than NATO.[102]

96. Kinne 2020.
97. Hartley and Sandler 1999, 674.
98. Singer 1987; Singer, Bremer, and Stuckey 1972.
99. Feenstra, Inklaar, and Timmer 2015.
100. Kinne 2018; Kinne and Bunte 2020.
101. Weidmann, Kuse, and Gleditsch 2010. Note that for all logged variables, we add 1 before transforming.
102. Leeds et al. 2002.

- NATO: a dummy variable that equals 1 if both i and j are NATO member states.
- UNGA IDEAL POINTS: the distance between the ideal-point estimates of i and j's voting records in the UN General Assembly.[103]
- TRADE: the total bilateral trade between i and j, log transformed.[104]
- DEMOCRACY$_j$: a dummy variable that equals 1 if the potential DCA partner is a democracy.[105]
- CAPABILITIES$_j$: the log-transformed Correlates of War Composite Indicator of National Capability score for j.[106]

The defense-spending equation of the ABM includes the exogenous covariate c_i. To operationalize this term, we draw on the empirical literature on defense spending, which emphasizes internal demand-side factors like political ideology, supply-side factors like economic growth, and exogenous factors like militarized conflict, alliance membership, and neighborhood effects. The following controls account for these influences:

- DEMOCRACY: a dummy variable that equals 1 if the country is democratic.[107] Because democracies face domestic challenges in diverting resources from "butter" to "guns," they may be less willing to spend on defense.[108]
- GDP GROWTH: the country's annual GDP growth rate.[109] *Ceteris paribus*, when governments have more revenue to spend, they spend more on defense.[110]
- ALLIANCES (NON-NATO): the number of alliances, excluding NATO, in which the country holds membership.[111] This variable accounts for potential spill-ins in formal alliances.[112]
- NATO MEMBER: a dummy variable that equals 1 if the country is a full NATO member state in the current year. NATO's unique institutional structure and expenditure guidelines may influence defense spending differently than other alliances.
- MILITARY REGIME: a dummy variable that equals 1 if the country's government is a military regime.[113] This variable accounts for militaristic political ideologies, which may be inclined toward high levels of defense spending.[114]

103. Bailey, Strezhnev, and Voeten 2017.
104. Barbieri and Keshk 2016; Barbieri, Keshk, and Pollins 2009.
105. Boix, Miller, and Rosato 2012.
106. Singer 1987.
107. Boix, Miller, and Rosato 2012.
108. Fordham and Walker 2005.
109. Feenstra, Inklaar, and Timmer 2015.
110. DiGiuseppe 2015; Whitten and Williams 2011.
111. Leeds et al. 2002.
112. Sandler and Hartley 2001, 873.
113. Geddes, Wright, and Frantz 2014.
114. Studies of defense spending often control for liberal/conservative government ideologies (e.g., Whitten and Williams 2011). Such metrics exclude autocratic regimes, which results in unacceptable levels of missing data.

- MIDS: the log-transformed count of the number of militarized interstate disputes in which the country participated in the current year.[115] Countries that frequently engage in conflict may spend more on defense.[116]
- SPATIAL LAG: the defense spending of the country's geographically contiguous neighbors. High levels of spending in neighboring states may increase spending in the focal state.[117]

The online supplement includes robustness checks with additional control variables, such as bilateral loans, alliance-based spill-ins, and alternative operationalizations of UNGA ideal points.

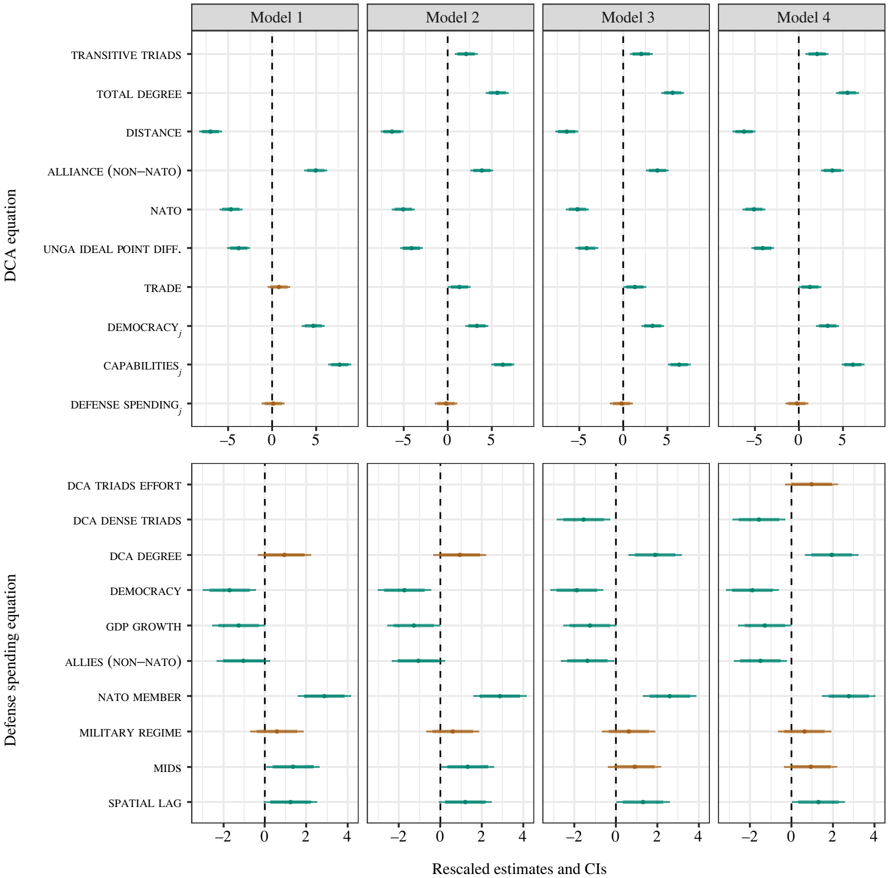
Results and Discussion

We estimated four models. Figure 8 summarizes the results, with estimates and confidence intervals scaled for legibility. (See the online supplement for unscaled estimates.) Model 1 is a baseline model that examines the coevolution of defense spending and DCA partner selection—via DEFENSE SPENDING$_j$ in the DCA equation and DCA DEGREE in the spending equation—but does not account for higher-order network effects. The estimates from the DCA equation show partial evidence of strategic selection. For example, the positive estimates for CAPABILITIES$_j$ and DEMOCRACY$_j$ indicate that governments prefer militarily capable and democratic defense partners.[118] The estimate for DEFENSE SPENDING$_j$ is statistically indistinguishable from zero. Governments do not appear to select high-spending partners.[119] The estimates for the remaining variables in the DCA equation are consistent with prior research.[120]

In the defense-spending equation of model 1 (lower panel), the estimate for DCA DEGREE is positive and weakly significant (10% level). This result is consistent with a bilateral influence effect and supports H1. Interpretation of SAOM estimates is analogous to multinomial logit. Exponentiating the (unscaled) estimates provides odds ratios. Consider a comparison between two hypothetical countries, *i* and *h*, equal on all observed dimensions except *i* has one more DCA tie than *h*. The unscaled estimate for DCA DEGREE (0.017) indicates that the odds of country *i* increasing its defense effort by one unit are about 1.7 percent greater than the odds of *h* increasing its defense effort. While this effect is small, large differences in DCA connectivity accumulate quickly. For example, if *i* has 10 more DCA ties than *h*, the odds of *i* increasing its defense effort are 19 percent greater than *h* doing so. If *i* has twenty

115. Palmer et al. 2015.
116. Nordhaus, Oneal, and Russett 2012.
117. Yesilyurt and Elhorst 2017.
118. Digiuseppe and Poast 2018.
119. However, when using absolute defense spending in lieu of the spending/GDP ratio, the estimate for DEFENSE SPENDING$_j$ is strongly positive. See the online supplement.
120. Kinne 2018; Kinne and Bunte 2020.

more DCA ties, the odds are over 40 percent greater. The more DCAs a state signs, the greater the pressure to increase defense effort.



Notes: Dots and lines are rescaled point estimates and confidence intervals. Thick lines are 95% confidence. Thin lines are 99% confidence. Estimates in green are significant at 95%. Estimates in brown are not significant. All individual convergence diagnostics < 0.1. Total convergence: model 1, 0.233; model 2, 0.238; model 3, 0.219; model 4, 0.232. See the online supplement for full table and unscaled estimates.

FIGURE 8. *Stochastic actor-oriented model of DCAs and defense spending*

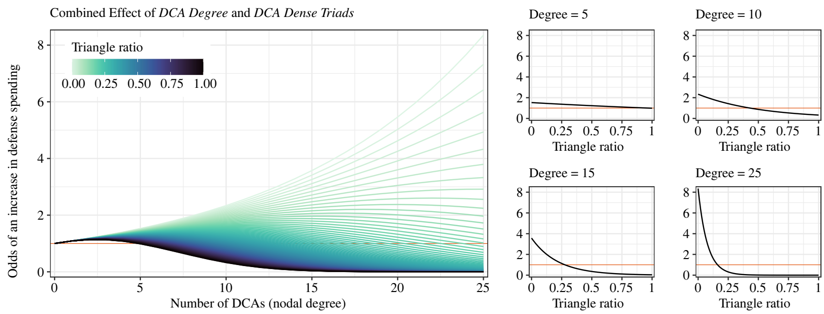
Model 2 introduces the main network selection term, TRANSITIVE TRIADS, along with the endogenous TOTAL DEGREE effect. This model estimates the extent to which countries condition their selection of DCA partners on structural features of the DCA network. The estimates for the network terms are large and highly precise, indicating a substantial network selection effect. Based on the estimate for TRANSITIVE TRIADS, the odds of a given country i selecting a partner j that shares a third party k in common are about 22 percent greater than the odds of i selecting an otherwise disconnected j, all else equal. This effect increases substantially as i and j's number of shared third-party collaborators increases. If i and j have, say, five DCA partners in common, the odds of i forming a DCA with j are nearly 170 percent greater than i's odds of selecting some disconnected partner. This selection effect reflects the attraction of network efficiencies.

Model 3 introduces the DCA DENSE TRIADS term into the defense spending equation, which indicates the effect of network structure on expenditures. The estimate is negative and highly significant. Substantively, adding one additional triangle lowers a country's odds of increasing its defense effort by about 2 percent. Adding ten triangles lowers those odds by 20 percent; adding twenty lowers them by 35 percent. Consistent with H2, dense local networks put downward pressure on defense effort. At the same time, model 3 shows a larger, more precise estimate for DCA DEGREE, which translates into a 9 percent increase in the odds of a one-unit increase in defense spending—substantially larger than the 1.7 percent effect found in model 1. The weakly positive estimate for DCA DEGREE in models 1 and 2 obscures the divergent effects of DCAs. Incorporating DCA DENSE TRIADS into the model not only reveals the influence of network structure but also permits a more precise estimate of bilateral influence.

Finally, model 4 incorporates the free-riding term, DCA TRIADS EFFORT. Contrary to H4, the estimate is statistically insignificant. And the estimate for DCA DENSE TRIADS remains virtually unchanged. We thus find no empirical evidence that dense local networks encourage states to free ride on the efforts of their defense partners. Rather, triangles as such reduce i's defense effort. This finding supports the more general efficiency mechanism, where network influence is a structural feature of states' respective local DCA networks and is not conditional on partners' spending. That said, the results here represent only a first step in assessing efficiency versus free riding; additional analyses may produce more nuanced conclusions. We consider extensions of this analysis in the conclusion.

Overall, the empirical results provide a comprehensive picture of how selection–influence dynamics combine with network effects to yield unexpected outcomes. At a purely bilateral level, states prefer capable defense partners. And when they sign agreements with those partners, *ceteris paribus*, their defense effort increases. Though contrary to standard public-goods logic, these findings are consistent with the logic of reciprocity-based punishment. Incorporating network-level dynamics, however, complicates the picture. States do not merely select capable partners; they also select partners in a way that yields transitive triads. Defense agreements signed within that context generate conflicting incentives. On the one hand, bilateral agreements pressure states to increase their defense effort and avoid punishments. On the other hand, dense local networks generate network efficiencies that lower the costs of defense production, thus encouraging reductions in spending.

To draw out the substantive implications of these findings, we conducted post-estimation analysis, focusing on the defense-spending equation. Because the free-riding term, DCA TRIADS EFFORT, showed no significant effect, we use model 3 for all post-estimation analysis. (The results for model 4 are virtually identical.) The key variables, DCA DEGREE and DCA DENSE TRIADS, are functions of one another; an accurate assessment of their respective influence requires that we consider both simultaneously. Further, the influence of transitive triads increases nonlinearly with nodal degree.[121] Thus, the countervailing effect of network structure on defense spending grows more pronounced as a node's local network densifies.



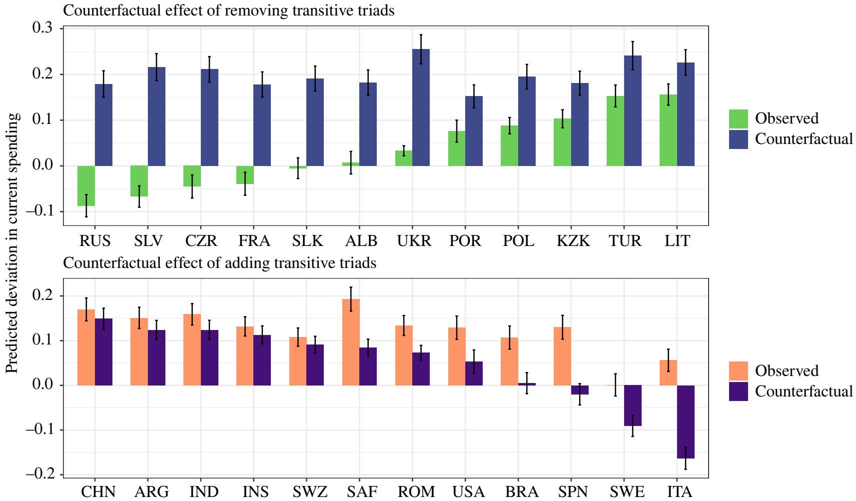
Notes: The left panel illustrates the odds of an increase in defense spending when comparing a country with zero degree to a country with degree d, where d is specified on the x axis. Triangle ratio is the actual number of triangles in a country's local network divided by the maximum possible number of triangles. The right panel illustrates the effect of $d \in \{5, 10, 15, 25\}$ on defense spending as the triangle ratio increases, using the same scale as in the left panel.

FIGURE 9. *Interpretation of degree and triangle effects on defense expenditures*

Figure 9 interprets the parameter estimates for DCA DEGREE and DCA DENSE TRIADS across a range of hypothetical degree and triangle values, holding all other variables constant. The left panel shows that the effect of DCAs varies sharply with network context. If a country increases its number of DCAs from zero to twenty-five, and those DCAs involve no transitive triads (that is, the ratio of actual to possible triangles in the country's local network is zero), then the odds of an increase in defense spending grow eight-fold, as shown in the top line. By contrast, if those twenty-five DCAs entail a maximal increase in triangles, as in a dense local network, then the odds of an increase in spending shrink to virtually zero.

The four panels on the right of Figure 9 illustrate the effect of triangles at fixed degrees. For a country with five DCAs, the odds of an increase in defense spending are greater than 1 for all but the very highest triangle ratios. For a country with ten DCAs, a triangle ratio of 0.4 or greater—indicating that 40 percent or more of the possible triangles in that country's local network in fact exist—pushes the odds of an increase in spending below the 1:1 threshold. And for a country with twenty-five DCAs, a triangle ratio of just 15 percent reduces the odds of an increase in spending from nearly 8:1 to 1:1. The more deeply embedded a country is in the DCA network, the more strongly network structure pushes against bilateral influence.

121. For a node with degree d, the maximum number of triangles in its local network is $d \times (d - 1)$.

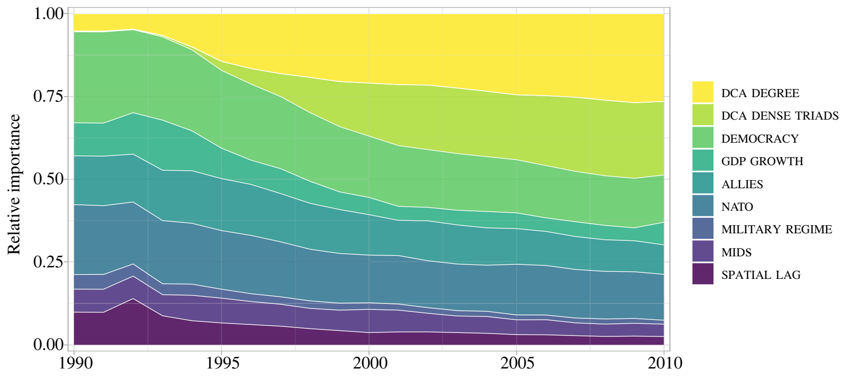


Notes: Estimates derived from 1,000 iterations of the 2010 network based on observed and counterfactual values of DCA DENSE TRIADS. Y axes indicate difference between predicted and actual levels of defense spending for each country, under each of the observed and counterfactual conditions. Top: for high-transitivity nodes, the counterfactual effect of removing all transitive triads in a node's local network while keeping degree at observed values. Bottom: for low-transitivity nodes, the counterfactual effect of increasing transitive triads by 50% while keeping degree at observed values.

FIGURE 10. *Counterfactual analysis of selected countries*

We also conducted counterfactual analysis using real-world cases (Figure 10). We selected twenty-four high-degree nodes in the 2010 network and split them into two groups: (1) those with high levels of transitivity in their respective local networks, and (2) those with low levels of transitivity. Such countries are especially vulnerable to counterfactual increases or decreases in triangles. Using observed values of all variables, we iteratively simulated the coevolution of the DCA network and defense spending, and we calculated the predicted level of spending for both groups. We then counterfactually *reduced* the triangle ratio for group 1 and *increased* the triangle ratio for group 2, and we again simulated coevolution and derived predictions.

Removing transitive triads (*top*) predicts a sharp upward deviation from current spending levels. For example, using observed values, the model predicts little change in Ukraine's defense spending. However, if Ukraine's local network altogether lacks transitive triads, the model predicts a substantial increase in spending. Put differently, Ukraine's level of defense spending—2.3 percent of GDP in 2010, less than most non-NATO former Soviet republics—is sustained, at least in part, by the structure of its defense relations. By contrast, adding transitive triads (*bottom*) attenuates that upward pressure—and for some states, pushes defense spending in a negative direction. For example, although Sweden's 2010 expenditures were already quite low (1.4% of GDP), the model predicts that increasing the density of its local network would push spending even lower. We emphasize that this



Notes: Variable importance as calculated by the Indlekofer-Brandes method. Scores scaled to sum to one for each year of observation. Estimates based on model 3.

FIGURE 11. *Relative importance of effects*

counter-factual exercise does not alter states' numbers of DCAs; it only manipulates the structure of their respective local networks.

Finally, to compare the influence of DCAs on defense spending to the influence of other components of the model, we assess variable importance.[122] Figure 11 illustrates the results. In the early 1990s, variations in defense spending were best explained by regime type, NATO membership, and alliances. While these influences continue to matter over time, their importance is gradually eclipsed by DCAs. By 2000, DCA DEGREE is the most important variable in the model. By 2009, DCA DEGREE and DCA DENSE TRIADS together explain nearly as much variation in defense spending as all other variables combined. (See the online supplement for variable importance by country.)

Conclusion

Burden sharing is an enduring collective-action problem. A network approach highlights aspects of burden sharing that, to our knowledge, have not been given extensive attention. Our main finding—that the effect of defense agreements on burden sharing depends on the network structure of those agreements—raises important questions about the overall provision of security. Our empirical results suggest that efficiencies, not free riding, are responsible for the negative effect of network structure on defense effort. Consequently, spending reductions do not necessarily indicate an underprovision of security. Rather, such reductions should

122. Indlekofer and Brandes 2013.

be viewed through the wider lens of network context; they may reflect the efficiency gains of densely connected networks. This insight complements the long-standing observation that efficiencies reduce aggregate spending even as overall provision of security remains optimal.[123]

This research is a first step toward merging network insights with established principles from the study of burden sharing, public goods, and collective action. While our ABM and empirical model implement a theoretically informed way of operationalizing efficiency and free riding, other approaches should be explored. In particular, further research is needed on whether defense networks improve security overall despite reductions in spending. Counterfactual estimates of optimal defense effort are notoriously difficult, even with well-defined institutions like NATO.[124] Such difficulties are amplified in a bilateral network context. A more promising approach, which we explore in related work,[125] is to consider whether dense local networks affect participation in bilateral defense actions, such as joint military exercises, arms trade, and peacekeeping operations. Such an analysis requires extensive dyadic data and a carefully specified causal-inference design. If the evidence indicates that defense activities increase among densely connected partners even as aggregate spending declines, states may indeed be producing more security at lower cost.

More broadly, our findings dovetail with recent work showing significant post–Cold War and post-9/11 shifts in how countries cooperate on defense, with a greater emphasis on nontraditional security threats and substantive defense activities.[126] Network influences are central to these trends.[127] While scholars have also examined network influences in traditional alliances,[128] the applicability of such studies to present-day security questions is limited by the relative lack of change in the global alliance network since the early 1990s. In a complex global environment, where interstate threats coexist alongside myriad nontraditional threats, efficient coordination of defense policies is an increasingly essential means of achieving security. Taken as a whole, our results suggest that bilateral agreements, when embedded within dense networks of aligned collaborators, may be a viable strategy for achieving optimal security gains.

Data Availability Statement

Replication files for this article may be found at <https://doi.org/10.7910/DVN/S0ILRB>.

123. Hartley and Sandler 1999, 669.
124. Hartley and Sandler 1999; Oneal 1990.
125. Kinne 2022.
126. Kinne 2020.
127. Kinne 2018.
128. Cranmer, Desmarais, and Kirkland 2012; Haim 2016; Warren 2016.

Supplementary Material

Supplementary material for this article is available at <https://doi.org/10.1017/S0020818322000315>.

References

Abercrombie, Cara. 2019. Realizing the Potential: Mature Defense Cooperation and the US-India Strategic Partnership. *Asia Policy* 14 (1):119–44.

Asikainen, Aili, Gerardo Iñiguez, Javier Ureña-Carrión, Kimmo Kaski, and Mikko Kivelä. 2020. Cumulative Effects of Triadic Closure and Homophily in Social Networks. *Science Advances* 6 (19): eaax7310.

Badev, Anton. 2021. Nash Equilibria on (Un)Stable Networks. *Econometrica* 89 (3):1179–206.

Bailey, Michael A., Anton Strezhnev, and Erik Voeten. 2017. Estimating Dynamic State Preferences from United Nations Voting Data. *Journal of Conflict Resolution* 61 (2):430–56.

Barabási, Albert-László, and Réka Albert. 1999. Emergence of Scaling in Random Networks. *Science* 286 (5439):509–12.

Barbieri, Katherine, and Omar M.G. Keshk. 2016. Correlates of War Project Trade Data Set Codebook, Version 4.0.

Barbieri, Katherine, Omar M.G. Keshk, and Brian M. Pollins. 2009. Trading Data: Evaluating Our Assumptions and Coding Rules. *Conflict Management and Peace Science* 26 (5):471–91.

Beardsley, Kyle, Howard Liu, Peter J. Mucha, David Siegel, and Juan Tellez. 2020. Hierarchy and the Provision of Order in International Politics. *Journal of Politics* 82 (2):731–46.

Bellais, Renaud, and Renelle Guichard. 2006. Defense Innovation, Technology Transfers and Public Policy. *Defence and Peace Economics* 17 (3):273–86.

Bennett, Colin J. 1991. What Is Policy Convergence and What Causes It? *British Journal of Political Science* 21 (2):215–33.

Benson, Brett V. 2012. *Constructing International Security: Alliances, Deterrence, and Moral Hazard*. Cambridge University Press.

Bianchi, Federico, Andreas Flache, and Flaminio Squazzoni. 2020. Solidarity in Collaboration Networks When Everyone Competes for the Strongest Partner: A Stochastic Actor-Based Simulation Model. *Journal of Mathematical Sociology* 44 (4):249–66.

Blair, Dennis C., and John T. Hanley. 2001. From Wheels to Webs: Reconstructing Asia-Pacific Security Arrangements. *Washington Quarterly* 24 (1):5–17.

Boix, Carles, Michael Miller, and Sebastian Rosato. 2012. A Complete Data Set of Political Regimes, 1800–2007. *Comparative Political Studies* 46 (12):1523–54.

Bramoullé, Yann, and Rachel Kranton. 2016. Games Played on Networks. In *The Oxford Handbook of the Economics of Networks*, edited by Yann Bramoullé, Andrea Galeotti, and Brian Rogers, 83–110. Oxford University Press.

Buchanan, James M. 1965. An Economic Theory of Clubs. *Economica* 32 (125):1–14.

Butts, Carter T. 2017. Comment: Actor Orientation and Relational Event Models. *Sociological Methodology* 47 (1):47–56.

Canen, Nathan, Matthew Jackson, and Francesco Trebbi. 2022. Social Interactions and Legislative Activity. *Journal of the European Economic Association* jvac051, https://doi.org/10.1093/jeea/jvac051.

Cao, Xun. 2017. Global Networks and Domestic Policy Convergence: A Network Explanation of Policy Changes. *World Politics* 64 (3):375–425.

Cecire, Michael H. 2016. The Bilateral Origins of South Caucasus Trilateralism. In *Turkish-Azerbaijani Relations: One Nation, Two States?* edited by Murad Ismayilov and Norman A. Graham, 72-87. Routledge.

Chowdhury, Abdur R. 1991. A Causal Analysis of Defense Spending and Economic Growth. *Journal of Conflict Resolution* 35 (1):80–97.

Chyzh, Olga. 2016. Dangerous Liaisons: An Endogenous Model of International Trade and Human Rights. *Journal of Peace Research* 53 (3):409–23.

Conybeare, John A. C. 1994. The Portfolio Benefits of Free Riding in Military Alliances. *International Studies Quarterly* 38 (3):405–19.

Conybeare, John A.C., James C. Murdoch, and Todd Sandler. 1994. Alternative Collective-Goods Models of Military Alliances: Theory and Empirics. *Economic Inquiry* 32 (4):525–42.

Cornes, Richard, and Todd Sandler. 1984. Easy Riders, Joint Production, and Public Goods. *Economic Journal* 94 (375):580–98.

Corning, Gregory P. 2020. Japan and Regulatory Convergence in TPP and JEEPA: Path Dependence, Complex Governance and Obstacles to Triadic Closure. *Cambridge Review of International Affairs*, https://doi.org/10.1080/09557571.2020.1854177

Cranmer, Skyler J., Bruce A. Desmarais, and Justin H. Kirkland. 2012. Toward a Network Theory of Alliance Formation. *International Interactions* 38 (3):295–324.

Crescenzi, Mark J.C., Jacob D. Kathman, Katja B. Kleinberg, and Reed M. Wood. 2012. Reliability, Reputation, and Alliance Formation. *International Studies Quarterly* 56 (2):259–74.

De Marchi, Scott, and Scott E. Page. 2014. Agent-Based Models. *Annual Review of Political Science* 17:1–20.

DiGiuseppe, Matthew. 2015. Guns, Butter, and Debt: Sovereign Creditworthiness and Military Expenditure. *Journal of Peace Research* 52 (5):680–93.

Digiuseppe, Matthew, and Paul Poast. 2018. Arms Versus Democratic Allies. *British Journal of Political Science* 48 (4):981–1003.

Drezner, Daniel W. 2001. Globalization and Policy Convergence. *International Studies Review* 3 (1):53–78.

Drezner, Daniel W. 2005. Globalization, Harmonization, and Competition: The Different Pathways to Policy Convergence. *Journal of European Public Policy* 12 (5):841–59.

Duque, Marina G. 2018. Recognizing International Status: A Relational Approach. *International Studies Quarterly* 62 (3):577–92.

Elkink, Johan A., and Thomas U. Grund. 2022. Modeling Diffusion Through Statistical Network Analysis: A Simulation Study and Empirical Application to Same-Sex Marriage. *International Studies Quarterly* 66 (1):sqab087.

Farrell, Henry, and Abraham L. Newman. 2019. Weaponized Interdependence: How Global Economic Networks Shape State Coercion. *International Security* 44 (1):42–79.

Fazal, Tanisha M., and Paul Poast. 2019. War Is Not Over: What the Optimists Get Wrong About Conflict. *Foreign Affairs* 98 (6):74–83.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. 2015. The Next Generation of the Penn World Table. *American Economic Review* 105 (10):3150–82.

Finn, Kelly R., Matthew J. Silk, Mason A. Porter, and Noa Pinter-Wollman. 2019. The Use of Multilayer Network Analysis in Animal Behaviour. *Animal Behaviour* 149:7–22.

Fordham, Benjamin O., and Thomas C. Walker. 2005. Kantian Liberalism, Regime Type, and Military Resource Allocation: Do Democracies Spend Less? *International Studies Quarterly* 49 (1):141–57.

Fuhrmann, Matthew. 2020. When Do Leaders Free-Ride? Business Experience and Contributions to Collective Defense. *American Journal of Political Science* 64 (2):416–31.

Galeotti, Andrea, Sanjeev Goyal, Matthew Jackson, Fernando Vega-Redondo, and Leeat Yariv. 2010. Network Games. *Review of Economic Studies* 77 (1):218–44.

Geddes, Barbara, Joseph Wright, and Erica Frantz. 2014. Autocratic Breakdown and Regime Transitions: A New Data Set. *Perspectives on Politics* 12 (2):313–31.

Greenhill, Brian. 2010. The Company You Keep: International Socialization and the Diffusion of Human Rights Norms. *International Studies Quarterly* 54 (1):127–45.

Greenhill, Brian, Layna Mosley, and Aseem Prakash. 2009. Trade-Based Diffusion of Labor Rights: A Panel Study, 1986–2002. *American Political Science Review* 103 (4):669–90.

Haim, Dotan A. 2016. Alliance Networks and Trade: The Effect of Indirect Political Alliances on Bilateral Trade Flows. *Journal of Peace Research* 53 (3):472–90.

Hartley, Keith, and Todd Sandler. 1999. NATO Burden-Sharing: Past and Future. *Journal of Peace Research* 36 (6):665–80.

Holland, Paul W., and Samuel Leinhardt. 1971. Transitivity in Structural Models of Small Groups. *Comparative Group Studies* 2 (2):107–24.

Hollway, James, and Johan Koskinen. 2016. Multilevel Embeddedness: The Case of the Global Fisheries Governance Complex. *Social Networks* 44:281–94.

Htwe, Nyi Nyi, Seunghoo Lim, and Makoto Kakinaka. 2020. The Coevolution of Trade Agreements and Investment Treaties: Some Evidence from Network Analysis. *Social Networks* 61:34–52.

Hura, Myron, Gary McLeod, Eric V. Larson, James Schneider, Daniel Gonzales, Daniel M. Norton, Jody Jacobs, et al. 2000. *Interoperability: A Continuing Challenge in Coalition Air Operations*. RAND.

Indlekofer, Natalie, and Ulrik Brandes. 2013. Relative Importance of Effects in Stochastic Actor-Oriented Models. *Network Science* 1 (3):278–304.

Jackson, Matthew. 2003. The Stability and Efficiency of Economic and Social Networks. In *Advances in Economic Design*, edited by Murat Surtel and Semih Koray, 319–61. Springer.

Jackson, Matthew, and Asher Wolinsky. 1996. A Strategic Model of Social and Economic Networks. *Journal of Economic Theory* 71 (1):44–74.

Jackson, Matthew, and Yves Zenou. 2015. Games on Networks. In *Handbook of Game Theory with Economic Applications*, edited by H. Peyton Young and Shmuel Zamir, 95–163. Elsevier.

Jung, Danielle F., and David A. Lake. 2011. Markets, Hierarchies, and Networks: An Agent-Based Organizational Ecology. *American Journal of Political Science* 55 (4):972–90.

Kahler, Miles. 1992. Multilateralism with Small and Large Numbers. *International Organization* 46 (3): 681–708.

Katz, Michael L., and Carl Shapiro. 1994. Systems Competition and Network Effects. *Journal of Economic Perspectives* 8 (2):93–115.

Keohane, Robert O. 1986. Reciprocity in International Relations. *International Organization* 40 (1):1–27.

Kinne, Brandon J. 2013. Network Dynamics and the Evolution of International Cooperation. *American Political Science Review* 107 (4):766–85.

Kinne, Brandon J. 2014. Dependent Diplomacy: Signaling, Strategy, and Prestige in the Diplomatic Network. *International Studies Quarterly* 58 (2):247–59.

Kinne, Brandon J. 2016. Agreeing to Arm: Bilateral Weapons Agreements and the Global Arms Trade. *Journal of Peace Research* 53 (3):359–77.

Kinne, Brandon J. 2018. Defense Cooperation Agreements and the Emergence of a Global Security Network. *International Organization* 72 (4):799–837.

Kinne, Brandon J. 2020. The Defense Cooperation Agreement Dataset (DCAD). *Journal of Conflict Resolution* 64 (4):729–55.

Kinne, Brandon J. 2022. Network Context and the Effectiveness of International Agreements. Working paper, University of California, Davis.

Kinne, Brandon J., and Jonas B. Bunte. 2020. Guns or Money? Defense Co-operation and Bilateral Lending as Coevolving Networks. *British Journal of Political Science* 50 (3):1067–88.

Kossinets, Gueorgi, and Duncan J. Watts. 2009. Origins of Homophily in an Evolving Social Network. *American Journal of Sociology* 115 (2):405–50.

Lai, Brian, and Dan Reiter. 2000. Democracy, Political Similarity, and International Alliances, 1816–1992. *Journal of Conflict Resolution* 44 (2):203–27.

Lake, David A. 2009. *Hierarchy in International Relations*. Cornell University Press.

Lazer, David. 2001. Regulatory Interdependence and International Governance. *Journal of European Public Policy* 8 (3):474–92.

Leeds, Brett Ashley. 2003. Do Alliances Deter Aggression? The Influence of Military Alliances on the Initiation of Militarized Interstate Disputes. *American Journal of Political Science* 47 (3):427–39.

Leeds, Brett Ashley, Jeffrey M. Ritter, Sara McLaughlin Mitchell, and Andrew G. Long. 2002. Alliance Treaty Obligations and Provisions, 1815–1944. *International Interactions* 28:237–60.

Lehmann, Todd C., James A. Rolfsen, and Terry D. Clark. 2015. Predicting the Trajectory of the Evolving International Cyber Regime: Simulating the Growth of a Social Network. *Social Networks* 41:72–84.

Loconto, Allison Marie. 2017. Models of Assurance: Diversity and Standardization of Modes of Intermediation. *Annals of the American Academy of Political and Social Science* 670 (1):112–32.

Loewen, Howard. 2018. Intra-Asia Pacific Defense Cooperation and the Emergence of a Second Order Security Architecture. In *The Changing East Asian Security Landscape*, edited by Stefan Fröhlich and Howard Loewen, 23–38. Springer.

Manger, Mark S., Mark A. Pickup, and Tom A.B. Snijders. 2012. A Hierarchy of Preferences: A Longitudinal Network Analysis Approach to PTA Formation. *Journal of Conflict Resolution* 56 (5): 853–78.

Maoz, Zeev. 2009. The Effects of Strategic and Economic Interdependence on International Conflict Across Levels of Analysis. *American Journal of Political Science* 53 (1):223–40.

Maoz, Zeev. 2012. Preferential Attachment, Homophily, and the Structure of International Networks, 1816–2003. *Conflict Management and Peace Science* 29 (3):341–69.

Mattes, Michaela. 2012. Reputation, Symmetry, and Alliance Design. *International Organization* 66 (4): 679–707.

Mearsheimer, John J. 2001. *The Tragedy of Great Power Politics*. 1st ed. Norton.

Milewicz, Karolina, James Hollway, Claire Peacock, and Duncan Snidal. 2018. Beyond Trade: The Expanding Scope of the Nontrade Agenda in Trade Agreements. *Journal of Conflict Resolution* 62 (4):743–73.

Murdie, Amanda. 2014. The Ties that Bind: A Network Analysis of Human Rights International Nongovernmental Organizations. *British Journal of Political Science* 44 (1):1–27.

Newman, Mark E.J. 2006. Modularity and Community Structure in Networks. *Proceedings of the National Academy of Sciences* 103 (23):8577–82.

Newman, Mark E.J., and M. Girvan. 2004. Finding and Evaluating Community Structure in Networks. *Physical Review E* 69. eprint: 0308217.

Niezink, Nynke M.D. 2018. Modeling the Dynamics of Networks and Continuous Behavior. PhD diss., University of Groningen.

Niezink, Nynke M.D., Tom A.B. Snijders, and Marijtje A.J. van Duijn. 2019. No Longer Discrete: Modeling the Dynamics of Social Networks and Continuous Behavior. *Sociological Methodology* 49 (1):295–340.

Nordhaus, William, John R. Oneal, and Bruce Russett. 2012. The Effects of the International Security Environment on National Military Expenditures: A Multicountry Study. *International Organization* 66 (3):491–513.

Olson, Mancur. 1965. *The Logic of Collective Action: Public Goods and the Theory of Groups*. Harvard University Press.

Olson, Mancur, and Richard Zeckhauser. 1966. An Economic Theory of Alliances. *Review of Economics and Statistics* 48 (3):266–79.

Oneal, John R. 1990. Testing the Theory of Collective Action: Nato Defense Burdens, 1950–1984. *Journal of Conflict Resolution* 34 (3):426–48.

Palmer, Glenn, Vito D'Orazio, Michael Kenwick, and Matthew Lane. 2015. The MID4 Dataset, 2002–2010: Procedures, Coding Rules and Description. *Conflict Management and Peace Science* 32 (2):222–42.

Pannier, Alice, and Olivier Schmitt. 2014. Institutionalised Cooperation and Policy Convergence in European Defence: Lessons from the Relations Between France, Germany and the UK. *European Security* 23 (3):270–89.

Porter, Patrick. 2019. Advice for a Dark Age: Managing Great Power Competition. *Washington Quarterly* 42 (1):7–25.

Pumpuni-Lenss, Gloria, Timothy Blackburn, and Andreas Garstenauer. 2017. Resilience in Complex Systems: An Agent-Based Approach. *Systems Engineering* 20 (2):158–72.

Ripley, Ruth M., Tom A.B. Snijders, Zsófia Boda, András Vörös, and Paulina Preciado. 2021. *Manual for RSiena*.

Rodrik, Dani. 2000. How Far Will International Economic Integration Go? *Journal of Economic Perspectives* 14 (1):177–86.

Sandler, Todd. 1993. The Economic Theory of Alliances: A Survey. *Journal of Conflict Resolution* 37 (3): 446–83.

Sandler, Todd. 2013. Buchanan Clubs. *Constitutional Political Economy* 24 (4):265–84.
Sandler, Todd, and John F. Forbes. 1980. Burden Sharing, Strategy, and the Design of NATO. *Economic Inquiry* 18 (3):425–44.
Sandler, Todd, and Keith Hartley. 2001. Economics of Alliances: The Lessons for Collective Action. *Journal of Economic Literature* 39 (3):869–96.
Satake, Tomohiko. 2011. The Origin of Trilateralism? The US-Japan-Australia Security Relations in the 1990s. *International Relations of the Asia-Pacific* 11 (1):1–28.
Simmel, Georg. 1950. *The Sociology of Georg Simmel*. Free Press.
Simon, Michael W., and Erik Gartzke. 1996. Political System Similarity and the Choice of Allies. *Journal of Conflict Resolution* 40 (4):617–35.
Singer, David J. 1987. Reconstructing the Correlates of War Dataset on Material Capabilities of States, 1916-1985. *International Interactions* 14 (2):115–32.
Singer, David J., Stuart A. Bremer, and John Stuckey. 1972. Capability Distribution, Uncertainty, and Major Power War, 1820-1965. In *Peace, War, and Numbers*, edited by Bruce Russett, 19–48. Sage.
Smith, Alastair. 1998. Extended Deterrence and Alliance Formation. *International Interactions* 24 (4):315–43.
Smith, Ron. 1995. The Demand for Military Expenditure. In *Handbook of Defense Economics*, edited by Keith Hartley and Todd Sandler, 69–87. Elsevier.
Snijders, Tom A.B. 2001. The Statistical Evaluation of Social Network Dynamics. *Sociological Methodology* 31:361–95.
Snijders, Tom A.B., and Christian E.G. Steglich. 2015. Representing Micro–Macro Linkages by Actor-Based Dynamic Network Models. *Sociological Methods and Research* 44 (2):222–71.
Stadtfeld, Christoph, Károly Takács, and András Vörös. 2020. The Emergence and Stability of Groups in Social Networks. *Social Networks* 60:129–45.
Steglich, Christian E.G., Tom A.B. Snijders, and Michael Pearson. 2010. Dynamic Networks and Behavior: Separating Selection from Influence. *Sociological Methodology* 40 (1):329–93.
Thompson, Alexander, and Daniel Verdier. 2014. Multilateralism, Bilateralism, and Regime Design. *International Studies Quarterly* 58 (1):15–28.
Verdier, Daniel. 2008. Multilateralism, Bilateralism, and Exclusion in the Nuclear Proliferation Regime. *International Organization* 62 (3):439–76.
Ward, Michael D., Randolph M. Siverson, and Xun Cao. 2007. Disputes, Democracies, and Dependencies: A Reexamination of the Kantian Peace. *American Journal of Political Science* 51 (3):583–601.
Warren, T. Camber. 2010. The Geometry of Security: Modeling Interstate Alliances as Evolving Networks. *Journal of Peace Research* 47 (6):697–709.
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):424–41.
Weidmann, Nils B., Doreen Kuse, and Kristian Skrede Gleditsch. 2010. The Geography of the International System: The CShapes Dataset. *International Interactions* 36 (1):86–106.
Whitten, Guy D., and Laron K. Williams. 2011. Buttery Guns and Welfare Hawks: The Politics of Defense Spending in Advanced Industrial Democracies. *American Journal of Political Science* 55 (1):117–34.
Wicker, McDaniel. 2016. Completing the Triangle: Security in Unity between the United States, South Korea, and Japan. Asia Program, Wilson Center.
Wilkins, Thomas S. 2015. From Strategic Partnership to Strategic Alliance? Australia-Japan Security Ties and the Asia-Pacific. *Asia Policy* 20 (1):81–112.
Winecoff, William Kindred. 2020. "The Persistent Myth of Lost Hegemony," Revisited: Structural Power as a Complex Network Phenomenon. *European Journal of International Relations* 26 (1, suppl.):209–52.
Wuthnow, Joel. 2019. US "Minilateralism" in Asia and China's Responses: A New Security Dilemma? *Journal of Contemporary China* 28 (115):133–50.
Yesilyurt, M. Ensar, and J. Paul Elhorst. 2017. Impacts of Neighboring Countries on Military Expenditures: A Dynamic Spatial Panel Approach. *Journal of Peace Research* 54 (6):777–90.
Zhang, J., L. Tong, P.J. Lamberson, R.A. Durazo-Arvizu, A. Luke, and D.A. Shoham. 2015. Leveraging Social Influence to Address Overweight and Obesity Using Agent-Based Models: The Role of Adolescent Social Networks. *Social Science and Medicine* 125:203–13.

Authors

Brandon J. Kinne is Associate Professor of Political Science at the University of California, Davis. He can be reached at bkinne@ucdavis.edu.
Stephanie N. Kang is a Postdoctoral Scholar in Political Science at the University of California, Davis. She can be reached at snkang@ucdavis.edu.

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Key Words

Defense cooperation; burden sharing; free riding; network efficiency; policy convergence; network analysis; network-behavior coevolution; stochastic actor-oriented model

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