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# The Optimal Defense of Networks of Targets<sup>1</sup>

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## **Abstract**

This paper examines a game-theoretic model of attack and defense of multiple networks of targets in which there exist intra-network strategic complementarities among targets. The defender's objective is to successfully defend all of the networks and the attacker's objective is to successfully attack at least one network of targets. Although there are multiple equilibria, we characterize correlation structures in the allocations of forces across targets that arise in all equilibria. For example, in all equilibria the attacker utilizes a stochastic 'guerrilla warfare' strategy in which a single random network is attacked.

**Keywords:** Allocation Game, Asymmetric Conflict, Attack and Defense, Colonel Blotto Game, Weakest-Link

# 1 Introduction

In the literature on game-theoretic models of attack and defense there has been a growing interest in the attack and defense of networks of targets. One focus of the work on the strategic role of network structure in this context is the role that strategic complementarities among targets play in creating structural asymmetries between the attack and defense of a network. For example in complex infrastructure networks — such as communication systems, electrical power grids, water and sewage systems, oil pipeline systems, transportation systems, and cyber security systems — there often exist particular targets or combinations of targets which if destroyed would be sufficient to either (a) disable the entire network or (b) create a terrorist “spectacular.”

The focus of this article is on strategic behavior in the attack and defense of a supra-network of targets made up of an arbitrary combination of two simple types of sub-networks. These two types capture the two extreme endpoints of an exposure-redundancy spectrum of network types. The maximal exposure network, which we label a *weakest-link network*, is successfully defended if and only if the defender successfully defends all targets within the network.<sup>1</sup> The maximal redundancy network, which we label a *best-shot network*, is successfully defended if and only if the defender successfully defends at least one target within the network. At each target the conflict is modeled as a deterministic contest in which the player who allocates the higher level of force wins the target with probability one. Given that the loss of a single network may be sufficient to either disable the entire supra-network or create a terrorist “spectacular,” we focus on the case in which the defender’s objective is to successfully defend all of the networks and the attacker’s objective is to successfully

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<sup>1</sup>See Hirshleifer (1983) who coins the terms best-shot and weakest-link in the context of the voluntary provision of public goods. Such best-shot and weakest-link complementarities arise in a number of environments. See for example the literature on group contests, e.g. Baik (2008), Baik et al. (2001), Barbieri et al. (2014), Chowdhury et al. (2013, 2016), Katz et al. (1990), Kolmar and Rommeswinkel (2013), Lee (2012), and Topolyan (2014).

attack at least one network of targets. That is, the supra-network is assumed to be *weakest link*.

We examine properties arising in the set of Nash equilibria of a simultaneous move game of attack and defense of the supra-network of targets. In this game the attacker's objective is to maximize the probability of winning at least one sub-network times his payoff for the successful attack of at least one sub-network,  $v_A$ , net of the expenditure on forces, which are allocated at a constant unit cost. Conversely, the defender's objective is to maximize the probability of preserving the entire supra-network times his payoff for successfully defending all sub-networks in the supra-network,  $v_D$ , net of his expenditure on forces, also allocated at constant unit cost. A distinctive feature of this environment is that a mixed strategy is a joint distribution function in which the randomization in the force allocation to each target is represented as a separate dimension. A pair of equilibrium joint distribution functions specifies not only each player's randomization in force expenditures to each target, but also the correlation structure of the force expenditures within and across the networks of targets. For all parameter configurations, we construct a Nash equilibrium pair of distribution functions and completely characterize the unique set of Nash equilibrium univariate marginal distributions and the unique equilibrium payoff of each player. Furthermore, we show that in any equilibrium the attacker launches an attack on at most one network within the supra-network and the resulting force allocation depends on the type of network attacked. In the event of an attack on a weakest-link network, the attacker optimally allocates a positive force level to only a single target within the network. When a best-shot network is attacked, the attacker optimally attacks every target in that network with a strictly positive force level.

Our results on endogenous force correlation structures in games of attack and defense are closely related to the literature on the classic Colonel Blotto game.<sup>2</sup> Originating with

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<sup>2</sup>Recent work on Blotto-type games includes extensions such as: asymmetric players (Roberson 2006, Hart 2008, Weinstein 2012, Dziubiński 2013, Macdonell and Mastronardi 2015), non-constant-sum variations (Kvasov 2007, Hortala-Vallve and Llorente-Saguer 2010, 2012, Roberson and Kvasov 2012), alternative

Borel (1921), the Colonel Blotto game is a two-player game in which each player allocates his fixed level of forces across a finite number of battlefields, within each battlefield the higher allocation wins, and each player maximizes the expected number of battlefield wins. As in our game of attack and defense, a mixed strategy is a joint distribution function. However, in the Colonel Blotto game it is the budget constraint that creates a linkage between the force allocations to the individual battlefields. Allocating force to a specific battlefield reduces the level of forces that can be allocated to other battlefields. Conversely, the linkages in our game of attack and defense arise because of the definition of success for each of the players.<sup>3</sup> Each player receives a “prize” if they win a critical number of battlefields. There are a number of related games that display similar objective-based linkages. For example, Szentes and Rosenthal (2003a) and Ewerhart (2017a) examine the so-called “chopstick auction” in which three identical objects are separately, but simultaneously, auctioned and each of two players wins a fixed prize of known and common value if and only if he wins at least two of the three objects. The player placing the highest bid on a given object wins the object. Szentes and Rosenthal (2003a) examine both winner-pay and all-pay versions of this auction. In the winner-pay version, a bid that does not win an object is refunded. In the all-pay version, all bids are forfeited. Ewerhart (2017a) constructs a new ‘fractal’ type of equilibrium for the chopsticks auction. Szentes and Rosenthal (2003b) examine a related  $n$ -player game in which each player’s objective is to secure a super-majority of auction wins. The model we examine here differs in that the critical number of battlefields is asymmetric across players.<sup>4</sup>

Our model features an environment in which random noise plays little role in determining

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definitions of success (Golman and Page 2009, Tang, Shoham, and Lin 2010, Rinott, Scarsini, and Yu 2012), and political economy applications (Laslier 2002, Laslier and Picard 2002, Roberson 2008, Thomas 2017).

<sup>3</sup>In a related attack and defense game, Bernhardt and Polborn (2010) examine a cost-based asymmetry between attack and defense. In that case, the “committed” attacker experiences no opportunity costs from allocating forces and continues attacking targets until either he runs out of targets or is defeated.

<sup>4</sup>See Kovenock and Roberson (2012) for a survey of cost- and objective-based linkages in multidimensional resource allocation games. See also Arce, Kovenock and Roberson (2012) which examines a related game with multiple attack technologies.

the outcomes at the targets — at each target the player with the largest resource expenditure for the target wins the target with certainty.<sup>5</sup> Closely related is the literature on simultaneous-move multidimensional resource allocation games in which the conflict at each target features a softer form of competition that emphasizes the role of random noise in determining the outcomes at the targets.<sup>6</sup> For example, under the Tullock contest success function (henceforth, CSF) the probability that a player wins a target is equal to the ratio of the player’s resource expenditure at the target to the sum of all of the players’ expenditures at the target. The case of the attack and defense of a single weakest-link network of targets with the outcome at each target determined by the Tullock CSF is examined by Clark and Konrad (2007) who find that under this softer form of competition the attacker optimally chooses a complete coverage strategy in which each and every target is attacked with certainty.

In contrast to Clark and Konrad (2007), we find that when the factors influencing target outcomes are explicitly captured in the model, with unmodeled factors or “noise” playing little or no role, attackers utilize a stochastic guerrilla warfare strategy in all equilibria, which for the special case that the supra-network consists of a single weakest-link network involves a single random target being attacked but with positive probability each target is chosen as the one to be attacked.<sup>7</sup> Interestingly, this single attack feature also arises in

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<sup>5</sup>This corresponds to the limiting case of the general ratio-form contest success function  $a^m/(a^m + d^m)$  where  $m$  is set to  $\infty$  and  $a$  and  $d$  are the two players’ allocations of force. The parameter  $m \in \mathbb{R}_+$  is inversely related to the level of noise in the conflict: low values imply a large amount of noise and high values correspond to low or no noise. Because (for a single contest with linear costs) pure-strategy equilibria fail to exist for all  $m$  greater than 2 and all equilibria in one-shot contests are payoff and revenue equivalent to the  $m = \infty$  case whenever  $m > 2$  (Ewerhart 2017b), the case of  $m = \infty$  is viewed as an important theoretical benchmark that is relevant for all  $m > 2$ .

<sup>6</sup>See for example Snyder (1989) and Klumpp and Polborn (2006) which examine related games featuring the symmetric majoritarian objective in the context of politicians engaged in a campaign resource allocation game.

<sup>7</sup>Kovenock, Roberson, Sheremeta (2010) experimentally examine behavior in a specification of the game of attack and defense of a single weakest-link network of targets where the conflict at each target is modeled by the Tullock CSF and the specification given in this paper with the auction CSF. Consistent with the theoretical prediction under the auction CSF, attackers utilize a stochastic guerrilla warfare strategy — in which a single random target is attacked — more than 80% of the time. Under the lottery CSF, attackers



Chowdhury and Topolyan (2016a) who examine a group-contest version of Clark and Konrad (2007) in which the force allocations of a group of attackers are aggregated according to the maximum effort, or best-shot, of the group and the force allocations of a group of defenders are aggregated according to the minimum effort, or weakest-link, of the group and successful attack or defense is a public good across the group of attackers and defenders respectively.<sup>8</sup> In that context, Chowdhury and Topolyan (2016a) find that free-riding effects among the group of attackers give rise to a single attacker allocating a strictly positive level of force in equilibrium.

Also related is the literature on sequential-move models of the attack and defense of a network of targets, in which the defender is an exogenously imposed leader — implying that the attacker’s force allocations can be made contingent on the defender’s allocation. Dziubiński and Goyal (2013, 2017) examine a three-stage game in which the defender first designs the network and then chooses which nodes to perfectly defend, where there is a constant per node cost of defense. Then, the attacker observes the network and its defense and chooses a subset of the undefended nodes to destroy, where there is a constant per node cost to attack. Dziubiński and Goyal (2013) shows that the equilibrium network design depends critically on the cost to attack and defend nodes, where for a range of parameters equilibrium features a star network with the center node being defended. Dziubiński and Goyal (2017) identify a class of networks that minimize conflict (as measured by total expenditures on attack and defense) and examine decentralized defense of the nodes. Hoyer and Jaegher (2016) examine a related two-stage game that differs in that the first stage network formation entails link formation costs, there is no (second-stage) defense, and the equilibrium network

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utilize the stochastic guerrilla warfare strategy almost 45% of the time, and the theoretical prediction of the attacker covering all of the targets is observed less than 30% of the time.

<sup>8</sup>See also Chowdhury and Topolyan (2016b) who examine a group all-pay auction with a weakest-link group versus a best-shot group. Note, however, that in group contests, each player makes a one-dimensional effort decision, and, thus, the group coordination issues arising in that setting fundamentally differ from the case of a single player making a multi-dimensional force allocation decision, which, in the case of a mixed strategy, may utilize a nontrivial correlation pattern among stochastic battlefield allocations.

design depends critically on the cost to form links and to attack nodes, where, for a range of parameters, a star network arises in equilibrium.

Acemoglu et al. (2016) and Goyal and Vigier (2014) examine sequential-move models that allow for attacks to be contagious, such as with a computer virus. The attacker observes defensive efforts and then either randomizes over where to attack (Acemoglu et al. 2016) or allocates resources across targets and the outcome at each target is determined by the Tullock CSF (Goyal and Vigier 2014). In Acemoglu et al. (2016) a group of individuals form the node set in a network with random links and each individual in the network makes an investment in security – that lowers the probability that an attack on a given node is successful. Decentralization is shown to result in over investment in defense in this setting. Conversely, in Goyal and Vigier (2014), there is a network designer who first designs the network and then allocates resources across the network. In equilibrium, the network is, for a range of parameters, a star network and all defensive resources are allocated to the center node. Lastly, in sequential-move reliability-theoretic models such as Bier et al. (2007), and Powell (2007a, b), defensive resources increase the stochastic reliability of a target in the event of an attack, the defender’s payoff is additive with respect to the values of the surviving targets, and it is exogenously specified that the attacker uses a guerrilla warfare strategy consisting of an attack on a single target. In the case that the defender has private information concerning the vulnerability of the individual targets, as in Powell (2007b), this sequential-move structure gives rise to an interesting signaling problem in that the defender would like to protect the most vulnerable targets but does not want to signal to the attacker which targets are the most vulnerable.

In contrast, our simultaneous-move model is motivated by applications such as information or transportation network defense or border defense, where attackers must either take actions before being certain of the allocation of defensive resources or where strategies like random monitoring or deployment may be employed by defenders and, thus, defensive re-

sources can either be concealed or randomly allocated with sufficient speed that it is difficult to argue that attacker allocations can be made contingent on defensive allocations. Furthermore, by endogenizing the attacker’s entry and force expenditure decisions, our approach sheds light not only on the conditions under which the assumption of one attack is likely to hold, but also related issues such as how the defender’s actions can decrease the number and/or intensity of attacks.

Section 2 presents the model of attack and defense with networks of targets. Section 3 characterizes a Nash equilibrium and explores properties of the equilibrium distributions of force. Section 4 concludes.

## 2 The Model

### Players

The model is formally described as follows. Two players, an attacker,  $A$ , and a defender,  $D$ , simultaneously allocate their forces across a finite number,  $n \geq 2$ , of heterogeneous targets. The players’ payoffs depend on the composition of each of the networks of targets in the supra-network. We examine a supra-network consisting of any arbitrary combination of two types of simple networks.

The targets are partitioned into a finite number  $k \geq 1$  of disjoint networks, where network  $j \in \{1, \dots, k\}$  consists of a finite number  $n_j \geq 1$  of targets with  $\sum_{j=1}^k n_j = n$ . Let  $N_j$  denote the set of targets in network  $j$ . Let  $\mathcal{W}$  denote the set of weakest-link networks and  $\mathcal{B}$  denote the set of best-shot networks.

In a *best-shot network* the network is successfully defended if the defender allocates at least as high a level of force to at least one target within the network. Conversely, an attack on a best-shot network is successful if the attacker allocates a higher level of force to each target in the network. Let  $x_A^i$  ( $x_D^i$ ) denote the level of force allocated by the attacker

(defender) to target  $i$ . Define

$$v_j^B = \begin{cases} 1 & \text{if } \forall i \in N_j \mid x_A^i > x_D^i \\ 0 & \text{otherwise} \end{cases}.$$

Observe that for each target, the player that allocates the higher level of force wins that target, but in order to win the network the attacker must win all of the targets. In a best-shot network, a tie arises when player  $A$  allocates a level of force to each target in the network that is at least as great as player  $D$ 's allocation, and there exists at least one target in the network to which the players allocate the same level of force. In this case, the defender wins the network.

In the second type of network, which we label a *weakest-link network*, the network is successfully defended if the defender allocates at least as high a level of force to all targets within the network. Conversely, an attack on a weakest-link network is successful if the attacker allocates a higher level of force to any target in the network. Define

$$v_j^W = \begin{cases} 1 & \text{if } \exists i \in N_j \mid x_A^i > x_D^i \\ 0 & \text{otherwise} \end{cases}.$$

Again, in the case of a tie, the defender is assumed to win the network.<sup>9</sup>

The players are risk neutral and have asymmetric objectives. The attacker's objective is to successfully attack at least one network, and the attacker's payoff for the successful attack

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<sup>9</sup>Note that for a given supra-network, our classification of weakest-link and best-shot networks is equivalent to alternative classifications such as: (1) combining all weakest-link networks into a single weakest-link network, because the attacker wins if any target in the set of weakest-link networks is lost or (2) replacing each weakest-link network with a collection of singleton target best-shot networks, one best-shot network for each target in the weakest-link network.

of at least one network is  $v_A > 0$ . The attacker's payoff function is given by

$$\pi_A(\mathbf{x}_A, \mathbf{x}_D) = v_A \max \left( \{t_j^B\}_{j \in \mathcal{B}}, \{t_j^W\}_{j \in \mathcal{W}} \right) - \sum_{i=1}^n x_A^i$$

The defender's objective is to preserve the entire supra-network, and the defender's payoff for successfully defending the supra-network is  $v_D > 0$ . The defender's payoff function is given by

$$\pi_D(\mathbf{x}_A, \mathbf{x}_D) = v_D \left( 1 - \max \left( \{t_j^B\}_{j \in \mathcal{B}}, \{t_j^W\}_{j \in \mathcal{W}} \right) \right) - \sum_{i=1}^n x_D^i.$$

The force allocated to each target must be nonnegative.

It is important to note that our formulation utilizes an auction contest success function.<sup>10</sup> It is well known that, because behavior is invariant with respect to positive affine transformations of utility, all-pay auctions in which players have different constant unit costs of resources may be transformed into behaviorally equivalent all-pay auctions with identical unit costs of resources, but suitably modified valuations. This result extends directly to the environment examined here, and thus, our focus on asymmetric valuations also covers the case in which the players have different constant unit costs of resources.

Also observe that in the formulation described above the supra-network is a weakest-link supra-network. That is if the defender loses a single network then the entire supra-network is inoperable. By interchanging the identities of player  $A$  and player  $D$ , our results on weakest-link supra-networks apply directly to the case of best-shot supra-networks (where a best-shot supra-network is a supra-network which is successfully defended if the defender successfully defends at least one network).

Figure 1 provides a representative supra-network consisting of 5 networks (A, B, C, D, and E). Networks A, C, and E are weakest-link (series) networks with two targets each. Networks B and D are best-shot (parallel) networks with five targets each. In order to

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<sup>10</sup>See Baye, Kovenock, and de Vries (1996).

preserve the entire supra-network player  $D$ 's objective is to preserve a path across the entire network. If a single target in networks A, C, or E is destroyed then the supra-network is inoperable. Conversely, in networks B and D all of the targets must be destroyed in order to render the supra-network inoperable.

[Insert Figure 1 here]

## Strategies

It is clear that there is no pure strategy equilibrium for this class of games. A mixed strategy, which we term a *distribution of force*, for player  $i$  is an  $n$ -variate distribution function  $P_i : \mathbb{R}_+^n \rightarrow [0, 1]$ . The  $n$ -tuple of player  $i$ 's allocation of force across the  $n$  targets is a random  $n$ -tuple drawn from the  $n$ -variate distribution function  $P_i$ .

## Model of Attack and Defense with Networks of Targets

The model of attack and defense with networks of targets, which we label

$$ADN \left\{ \{N_j\}_{j \in \mathcal{B}}, \{N_j\}_{j \in \mathcal{W}}, v_A, v_D \right\},$$

is the one-shot game in which players compete by simultaneously announcing distributions of force, each target is won by the player that provides the higher allocation of force for that target, ties are resolved as described above, and players' payoffs,  $\pi_A$  and  $\pi_D$ , are specified above.

### 3 Optimal Distributions of Force

It is useful to introduce a simple summary statistic that captures both the asymmetry in the players' valuations and the structural asymmetries arising in the supra-network.

**Definition 1.** Let  $\alpha = v_D / (v_A [\sum_{j \in \mathcal{W}} n_j + \sum_{j \in \mathcal{B}} \frac{1}{n_j}])$  denote the normalized relative strength of the defender.

Several properties of this summary statistic should be noted. First, the normalized relative strength of the defender is increasing in the relative valuation of the defender to the attacker ( $v_D/v_A$ ), and is decreasing in the level of exposure arising in the supra-network ( $\sum_{j \in \mathcal{W}} n_j + \sum_{j \in \mathcal{B}} \frac{1}{n_j}$ ). In particular, the defender's exposure is increasing in the number of weakest-link targets ( $\sum_{j \in \mathcal{W}} n_j$ ), and is decreasing in the number of targets within each best-shot network ( $\sum_{j \in \mathcal{B}} \frac{1}{n_j}$ ).

For all parameter ranges, Theorem 1 establishes the uniqueness of: (i) the players' equilibrium expected payoffs and (ii) the players' sets of univariate marginal distributions. Theorem 1 also provides a pair of equilibrium distributions of force for all parameter ranges. Case (1) of Theorem 1 examines the parameter configurations for which the defender has a normalized relative strength advantage, i.e.  $\alpha \geq 1$ . Case (2) of Theorem 1 addresses the parameter configurations for which the defender has a normalized relative strength disadvantage, i.e.  $\alpha < 1$ . It is important to note that the stated equilibrium distributions of force ( $n$ -variate distributions) are not unique. However, in Propositions 1-3 we characterize properties of optimal attack and defense that hold in all equilibria.

**Theorem 1.** For any feasible parameter configuration of the game  $ADN\{\{N_j\}_{j \in \mathcal{B}}, \{N_j\}_{j \in \mathcal{W}}, v_A, v_D\}$  there exists a unique set of Nash equilibrium univariate marginal distributions and a unique equilibrium payoff for each player. One such equilibrium is for each player to allocate his forces according to the following  $n$ -variate distribution functions:

(1) If  $\alpha \geq 1$ , then for player A and  $\mathbf{x} \in \prod_{j \in \mathcal{W}} [0, v_A]^{n_j} \times \prod_{j \in \mathcal{B}} [0, \frac{v_A}{n_j}]^{n_j}$

$$P_A(\mathbf{x}) = 1 - \frac{1}{\alpha} + \frac{\sum_{j \in \mathcal{W}} \sum_{i \in N_j} x^i + \sum_{j \in \mathcal{B}} \min_{i \in N_j} \{x^i\}}{v_D}$$

Similarly for player D and  $\mathbf{x} \in \prod_{j \in \mathcal{W}} [0, v_A]^{n_j} \times \prod_{j \in \mathcal{B}} [0, \frac{v_A}{n_j}]^{n_j}$

$$P_D(\mathbf{x}) = \min \left( \left\{ \frac{\min_{i \in N_j} \{x^i\}}{v_A} \right\}_{j \in \mathcal{W}}, \left\{ \frac{\sum_{i \in N_j} x^i}{v_A} \right\}_{j \in \mathcal{B}} \right)$$

The expected payoff for player A is 0, and the expected payoff for player D is  $v_D(1 - \frac{1}{\alpha})$ .

(2) If  $\alpha < 1$ , then for player A and  $\mathbf{x} \in \prod_{j \in \mathcal{W}} [0, \alpha v_A]^{n_j} \times \prod_{j \in \mathcal{B}} [0, \frac{\alpha v_A}{n_j}]^{n_j}$

$$P_A(\mathbf{x}) = \frac{\sum_{j \in \mathcal{W}} \sum_{i \in N_j} x^i + \sum_{j \in \mathcal{B}} \min_{i \in N_j} \{x^i\}}{v_D}$$

Similarly for player D and  $\mathbf{x} \in \prod_{j \in \mathcal{W}} [0, \alpha v_A]^{n_j} \times \prod_{j \in \mathcal{B}} [0, \frac{\alpha v_A}{n_j}]^{n_j}$

$$P_D(\mathbf{x}) = 1 - \alpha + \min \left( \left\{ \frac{\min_{i \in N_j} \{x^i\}}{v_A} \right\}_{j \in \mathcal{W}}, \left\{ \frac{\sum_{i \in N_j} x^i}{v_A} \right\}_{j \in \mathcal{B}} \right)$$

The expected payoff for player D is 0, and the expected payoff for player A is  $v_A(1 - \alpha)$ .

*Proof.* The proof of the uniqueness of the players' equilibrium expected payoffs and sets of univariate marginal distributions is given in the Appendix. We now establish that the pair of  $n$ -variate distribution functions given in case (1) constitute an equilibrium for  $\alpha \geq 1$ . The proof of case (2) is analogous. The Appendix (see Lemma 5) establishes that in any  $n$ -tuple drawn from any equilibrium  $n$ -variate distribution  $P_A$  player A allocates a strictly positive level of force to at most one network of targets. If the network which receives the strictly positive level of force is a weakest-link network, then exactly one target in that network receives a strictly positive level of force. Although not a necessary condition for equilibrium,



the  $P_A$  described in Theorem 1 also displays the property that when the network which receives the strictly positive level of force is a best-shot network the force allocated to each target in that network is an almost surely increasing function of the force allocated to any of the other targets in that network. The Appendix (see Lemma 5) also establishes that in any  $n$ -tuple drawn from any equilibrium  $n$ -variate distribution  $P_D$  player  $D$  allocates a strictly positive level of force to at most one target in each best-shot network of targets.

We will now show that for each player each point in the support of their equilibrium  $n$ -variate distribution function,  $P_A$  or  $P_D$ , given in case (1) of Theorem 1 results in the same expected payoff, and then show that there are no profitable deviations from this support.

We begin with the case in which player  $A$  attacks a single target in a single weakest-link network. The probability that player  $A$  wins target  $i$  in network  $j \in \mathcal{W}$  is given by the univariate marginal distribution  $P_D(x_A^i, \{\{v_A\}_{i' \in N_{j'} | x_{A'}^{i'}=0}\}_{j' \in \mathcal{W}}, \{\{\frac{v_A}{n_{j'}}\}_{i' \in N_{j'}}\}_{j' \in \mathcal{B}})$ , which we denote as  $P_D^i(x_A^i)$ . Given that player  $D$  is using the equilibrium strategy  $P_D$  described above, the payoff to player  $A$  for any allocation of force  $\mathbf{x}_A \in \mathbb{R}_+^n$  which allocates a strictly positive level of force to a single target  $i$  in a weakest-link network  $j \in \mathcal{W}$  is

$$\pi_A(\mathbf{x}_A, P_D) = v_A P_D^i(x_A^i) - x_A^i.$$

Simplifying,

$$\pi_A(\mathbf{x}_A, P_D) = v_A \left( \frac{x_A^i}{v_A} \right) - x_A^i = 0.$$

Thus the expected payoff to player  $A$  from allocating a strictly positive level of force to only one target in any weakest-link network is 0 regardless of which target is attacked.

Next, we examine the case in which player  $A$  attacks a single best-shot network. The probability that player  $A$  wins every target in network  $j \in \mathcal{B}$  is given by the  $n_j$ -variate marginal distribution  $P_D(\{x_A^i\}_{i \in N_j}, \{\{v_A\}_{i' \in N_{j'}}\}_{j' \in \mathcal{W}}, \{\{\frac{v_A}{n_{j'}}\}_{i' \in N_{j'}}\}_{j' \in \mathcal{B} | j' \neq j})$ , which we denote as  $P_D^{N_j}(\{x_A^i\}_{i \in N_j})$ . Given that player  $D$  is using the equilibrium strategy  $P_D$  described above,

the payoff to player  $A$  for any allocation of force  $\mathbf{x}_A \in \mathbb{R}_+^n$  which allocates a strictly positive level of force only to the targets in a best-shot network  $j \in \mathcal{B}$ , and allocates zero forces to every other network is

$$\pi_A(\mathbf{x}_A, P_D) = v_A P_D^{N_j}(\{x_A^i\}_{i \in N_j}) - \sum_{i \in N_j} x_A^i.$$

Simplifying,

$$\pi_A(\mathbf{x}_A, P_D) = v_A \left( \frac{\sum_{i \in N_j} x_A^i}{v_A} \right) - \sum_{i \in N_j} x_A^i = 0.$$

Thus, the expected payoff to player  $A$  from allocating a strictly positive level of force to only one best-shot network is 0 regardless of which best-shot network is attacked.

For player  $A$ , possible deviations from the support include allocating a strictly positive level of force to: (a) two or more targets in the same weakest-link network, (b) two or more targets in different weakest-link networks, (c) two or more best-shot networks, and (d) any combination of both weakest-link and best-shot networks.

Beginning with (a), the probability that player  $A$  wins both targets  $i$  and  $i'$  in network  $j \in \mathcal{W}$  is given by the bivariate marginal distribution  $P_D(x_A^i, x_A^{i'}, \{\{v_A\}_{i'' \in N_{j'} | i'' \neq i, i'}\}_{j' \in \mathcal{W}}, \{\{\frac{v_A}{n_{j'}}\}_{i'' \in N_{j'}}\}_{j' \in \mathcal{B}})$ , which we denote as  $P_D^{i, i'}(x_A^i, x_A^{i'})$ . The payoff to player  $A$  for any allocation of force  $\mathbf{x}_A \in \mathbb{R}_+^n$  which allocates a strictly positive level of force to two targets  $i, i'$  in a weakest-link network  $j \in \mathcal{W}$  is

$$\pi_A(\mathbf{x}_A, P_D) = v_A P_D^i(x_A^i) + v_A P_D^{i'}(x_A^{i'}) - v_A P_D^{i, i'}(x_A^i, x_A^{i'}) - x_A^i - x_A^{i'}.$$

Simplifying,

$$\pi_A(\mathbf{x}_A, P_D) = v_A \left( \frac{x_A^i}{v_A} + \frac{x_A^{i'}}{v_A} - \frac{\min\{x_A^i, x_A^{i'}\}}{v_A} \right) - x_A^i - x_A^{i'} < 0.$$

The case of player  $A$  allocating a strictly positive level of force to more than two targets in a weakest-link network follows directly. Clearly, in any optimal strategy player  $A$  never allocates a strictly positive level of force to more than one target within a weakest-link network.

The proof for type (b) deviations follows along similar lines. Thus, in any optimal strategy player  $A$  never allocates a strictly positive level of force to more than one target within a weakest-link network of targets or in different weakest-link networks.

For type (c) deviations, the probability that player  $A$  wins all of the targets in both best-shot networks  $j, j' \in \mathcal{B}$  is given by the  $(n_j + n_{j'})$ -variate marginal distribution  $P_D(\{\{x_A^i\}_{i \in N_j \cup N_{j'}}, \{\{v_A\}_{i'' \in N_{j''}}\}_{j'' \in \mathcal{W}}, \{\{\frac{v_A}{n_{j''}}\}_{i'' \in N_{j''}}\}_{j'' \in \mathcal{B} | j'' \neq j, j'}\})$ , which we denote as  $P_D^{N_j, N_{j'}}(\{\{x_A^i\}_{i \in N_j \cup N_{j'}}\})$ . The payoff to player  $A$  for any allocation of force  $\mathbf{x}_A \in \mathbb{R}_+^n$  which allocates a strictly positive level of force to exactly two best-shot networks  $j, j' \in \mathcal{B}$  is

$$\pi_A(\mathbf{x}_A, P_D) = v_A P_D^{N_j}(\{\{x_A^i\}_{i \in N_j}\}) + v_A P_D^{N_{j'}}(\{\{x_A^i\}_{i \in N_{j'}}\}) - v_A P_D^{N_j, N_{j'}}(\{\{x_A^i\}_{i \in N_j \cup N_{j'}}\}) - \sum_{i \in N_j \cup N_{j'}} x_A^i.$$

Simplifying,

$$\pi_A(\mathbf{x}_A, P_D) = -v_A \min \left\{ \frac{\sum_{i \in N_j} x_A^i}{v_A}, \frac{\sum_{i \in N_{j'}} x_A^i}{v_A} \right\}$$

The case of player  $A$  allocating a strictly positive level of force to more than two best-shot networks follows directly. Clearly, in any optimal strategy player  $A$  never allocates a strictly positive level of force to more than one best-shot network.

The case of type (d), follows along similar lines. Thus, the expected payoff from each point in the support of the  $n$ -variate distribution  $P_A$  results in the same expected payoff, 0, and there exist no allocations of force which have a higher expected payoff.

The case for player  $D$  follows along similar lines. □

Although the equilibrium distributions of force stated in Theorem 1 are not unique,<sup>11</sup> it is useful to provide some intuition regarding the existence of this particular equilibrium before moving on to the characterization of properties of optimal attack and defense that hold in all equilibria (Propositions 1-3). The supports of the equilibrium distributions of force stated in Theorem 1 are given in Figure 2 for two different parameter configurations. Panels (i) and (ii) of Figure 2 provide the supports for the attacker and defender, respectively, in the case that there is one weakest-link network with two targets ( $i = 1, 2$ ). Panels (iii) and (iv) of Figure 2 provide the supports for the attacker and defender, respectively, in the case that there is one best-shot network with two targets ( $i = 1, 2$ ) and one weakest-link network with one target ( $i = 3$ ).

[Insert Figure 2]

Across all of the Panels (i)-(iv), if  $\alpha = 1$  then each player randomizes continuously over their respective shaded line segments. In the event that the defender has a normalized relative strength advantage ( $\alpha > 1$ ), the defender's strategy stays the same, but the attacker now places a mass point of size  $1 - (1/\alpha)$  at the origin and randomizes continuously over the respective line segments with the remaining probability. Conversely, if the defender has a normalized relative strength disadvantage ( $\alpha < 1$ ) then it is the defender who places a mass point (of size  $1 - \alpha$ ) at the origin.

Beginning with Panels (i) and (ii), recall that if the attacker successfully attacks a single target in a weakest-link network the entire network is disabled. As shown in Panel (i) the

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<sup>11</sup>For example, in the case (1) parameter range of Theorem 1 another equilibrium strategy for player  $D$  is to use the distribution of force

$$P_D(\mathbf{x}) = \min \left( \left\{ \frac{\prod_{i \in N_j} x^i}{v_A} \right\}_{j \in \mathcal{W}}, \left\{ \frac{\sum_{i \in N_j} x^i}{v_A} \right\}_{j \in \mathcal{B}} \right).$$

attacker launches an attack on at most one target. To successfully defend a weakest-link network, the defender must win every target within the network. As shown in Panel (ii) the defender's allocation of force to target  $i$  is an almost surely strictly increasing function of the force allocated to target  $-i$ . Note that if the attacker launches an attack on at most one target, then the probability that any single attack is successful depends only on the univariate marginal distributions of the defender's ( $n$ -variate joint) distribution of force. In addition, the defender's expected force expenditure depends only on his set of univariate marginal distributions, and, for a given set of univariate marginal distributions, is invariant to the correlation structure.<sup>12</sup> Finally, note that given the defender's choice of correlation structure [Panel (ii)], the attacker's probability of at least one successful attack depends only on the maximum of his force allocations across the two targets. That is, given the defender's distribution of force, if the set of points such that  $x_A^i > x_A^{-i} > 0$  for some  $i \in \{1, 2\}$  has positive probability, then the attacker can strictly increase his expected payoff by reducing  $x_A^{-i}$  to  $x_A^{-i} = 0$  for all such points. In such a deviation, the probability of at least one successful attack is unaffected, but the attacker's expected force expenditure decreases. Thus, at each point in the support of an optimal distribution of force the attacker launches at most one attack.

Panels (iii) and (iv) examine a simple supra-network with one best-shot network and one weakest-link network. In Panel (iii), note that the attacker launches an attack on at most one network. In the event that the best-shot network is attacked, the attacker's allocation of force to target  $i$  in the best-shot network is an almost surely strictly increasing function of the force allocated to target  $-i$  in the network. In Panel (iv), note that the defender allocates a strictly positive level of force to at most one of the targets  $i \in \{1, 2\}$  in the best-shot network, and that the level of force allocated to the sole target in the weakest-link

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<sup>12</sup>More formally, for a given set of univariate marginal distribution functions, the expected force expenditure is invariant to the mapping into a joint distribution function, i.e. the  $n$ -copula. For further details see Nelsen (2006).

network is an almost surely increasing function of the level of force allocated to the best-shot network. Given these correlation structures, the intuition for why the attacker launches an attack on at most one network in the supra-network follows along the lines given above for the weakest-link network in which at most one target was attacked.

We now characterize the qualitative features arising in all equilibrium distributions of force. Proposition 1 examines the number of networks that are simultaneously attacked as well as the number of targets within each network that are simultaneously attacked and defended. Propositions 2 and 3 examine the likelihood that the attacker optimally chooses to launch an attack on any given network, and the likelihood that the attacker launches no attack or the defender leaves the supra-network undefended.

**Proposition 1.** *In any equilibrium  $\{P_A, P_D\}$ :*

1. *Player A allocates a strictly positive level of force to at most one network.*
2. *If player A allocates a strictly positive level of force to a weakest-link network, then one target in that network receives a strictly positive level of force*
3. *In each best-shot network player D allocates a strictly positive level of force to at most one target in the network.*

The formal proof of Proposition 1 is given in the appendix (see Lemma 5). The intuition for Proposition 1 follows from the fact that the likelihood that player  $D$  successfully defends all of the networks (and therefore player  $D$ 's expected payoff) is weakly decreasing in the number of networks that player  $A$  chooses to simultaneously attack. However, player  $D$  has the ability to vary the correlation structure of his force allocations while leaving invariant: (i) his network specific multivariate marginal distributions of force, (ii) his univariate marginal distributions of force, and (iii) his expected expenditure. Furthermore, there exist correlation structures for which the likelihood that player  $D$  successfully defends all of the networks

depends only on player  $A$ 's force allocation to the one network which receives the highest level of force from player  $A$ . Given that player  $D$  is using such a correlation structure, player  $A$  optimally attacks at most one network at a time.

**Proposition 2.** *If  $\alpha \geq 1$ , then in any equilibrium  $\{P_A, P_D\}$ :*

1. *The probability that any weakest-link network  $j$  is attacked (i.e., the probability that the attacker allocates a strictly positive level of force to weakest-link network  $j$ ) is  $(n_j v_A / v_D)$ , which is increasing in the number of targets in network  $j$  and the attacker's valuation of success and decreasing in the defender's valuation of successfully defending the entire supra-network.*
2. *The probability that any best-shot network  $j$  is attacked is  $(v_A) / (n_j v_D)$ , which is increasing in the attacker's valuation of success and is decreasing in both the defender's valuation and the number of targets in network  $j$ .*
3. *The attacker optimally attacks no network in the supra-network with probability  $1 - (1/\alpha)$ .*

In the Appendix, we provide the univariate marginal distributions that arise in any equilibrium joint distribution of the attacker. Moreover, we show that if  $\alpha > 1$ , then in any equilibrium the attacker places a mass point at the origin. Proposition 2 follows directly. The probability that a network  $j$  is attacked is equal to one minus the attacker's mass point at zero in the  $n_j$ -variate marginal distribution for network  $j$ ,  $P_A^{N_j}(\{x_i\}_{i \in N_j})$ . The likelihood that the attacker optimally chooses to launch no attack is increasing in the defender's valuation of success and decreasing in the attacker's valuation of success.

For  $\alpha \geq 1$ , the attacker's valuation is low enough relative to the defender's valuation that the optimal strategy includes not launching an attack with positive probability. For  $\alpha < 1$ , the attacker optimally launches an attack with certainty. In this case the probability that any

given network of targets is attacked depends only on the number of targets in the network and the type of network. The proof of Proposition 3 also follows from the characterization of the properties of equilibrium joint distributions given in the Appendix.

**Proposition 3.** *If  $\alpha < 1$ , then in any equilibrium  $\{P_A, P_D\}$ :*

1. *The probability that any weakest-link network  $j$  is attacked (i.e., the probability that the attacker allocates a strictly positive level of force to weakest-link network  $j$ ) is  $n_j / ([\sum_{j' \in \mathcal{W}} n_{j'} + \sum_{j' \in \mathcal{B}} \frac{1}{n_{j'}}])$ , which is increasing in the number of targets in network  $j$ .*
2. *The probability that any best-shot network  $j$  is attacked is  $1 / (n_j [\sum_{j' \in \mathcal{W}} n_{j'} + \sum_{j' \in \mathcal{B}} \frac{1}{n_{j'}}])$ , which is decreasing in the number of targets in network  $j$ .*
3. *The defender optimally leaves the entire supra-network undefended with probability  $1 - \alpha$ .*

If  $\alpha \geq 1$ , the defender optimally chooses, with certainty, to allocate a strictly positive level of defensive force. However, if  $\alpha < 1$ , the defender optimally chooses to leave the entire supra-network undefended with positive probability. Furthermore, the likelihood that the defender chooses to leave the entire supra-network undefended is increasing in the attacker's valuation of success and decreasing in the defender's valuation of successfully defending the entire supra-network.

To summarize, the following conditions hold in all equilibria. If  $\alpha > 1$  the attacker optimally chooses not to launch an attack with positive probability. Regardless of the value of  $\alpha$ , the attacker optimally launches an attack on at most one network. In the event that a weakest-link network is attacked, only one target within the network is attacked. The likelihood that any individual network is attacked depends on the number of targets within the network. In each weakest-link network the likelihood of attack is increasing in the number



of targets. In each best-shot network the likelihood of attack is decreasing in the number of targets. If  $\alpha < 1$ , the defender optimally leaves the entire supra-network undefended with positive probability. Lastly, regardless of the value of  $\alpha$ , when the defender chooses to defend the supra-network, within each best-shot network, the defender randomly chooses at most one target to defend.

## 4 Conclusion

This paper examines a game-theoretic model of attack and defense of a supra-network, made up of a combination of weakest-link and best-shot networks of targets. The model features asymmetric objectives: the defender wishes to successfully defend all networks and the attacker's objective is to successfully attack at least one network. Although the model allows for general correlation structures for force expenditures within and across the networks of targets, for any such configuration of networks, we derive the unique equilibrium expected payoffs of the attacker and defender and demonstrate that there exists a unique equilibrium univariate marginal distribution of forces to each target. An equilibrium pair of strategies for the attacker and defender, each of which is a joint distribution governing the allocation of forces to all targets, is also constructed, although these are generally non-unique.

Our approach leads to a wealth of interesting extensions and applications. Because the game examined here is a set of complete information all-pay auctions linked by payoff complementarities, almost any extension of the standard one-dimensional strategic allocation problem represented by the standard all-pay auction with complete information has a corresponding extension in this game. Examples include, incomplete information, about values or unit costs of forces, affine handicapping of players within target contests, and nonlinear costs of forces.<sup>13</sup> In addition, as in other models of strategic multidimensional resource allocation,

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<sup>13</sup>Examples of these extensions for the one-dimensional strategic allocation problem include Amann and Leininger (1996), Krishna and Morgan (1997), Moldovanu and Sela (2001, 2006), Gale and Stegeman (1994),

such as Colonel Blotto games, interesting extensions arise by introducing more heterogeneity across targets, such as allowing for differential target values for attacker and defender within the weakest-link and best-shot structure, or other linkages across targets, such as budget constraints or “infrastructure technologies” that allow lumpy force expenditure across sets of multiple targets or networks. Furthermore, because our model succeeds in pinning down unique equilibrium payoffs for arbitrary network configurations and player valuations, it readily serves as a component model for multistage models of network investment, where uniqueness of subgame equilibrium payoffs avoids a multiplicity of equilibria supported by finite horizon trigger strategies. Hence, theories of strategic network investment and systems redundancies may be simply addressed in the framework, in which each best shot network  $j$  employed may be viewed as a network with  $n_j - 1$  redundant components.

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## Appendix

This appendix characterizes the supports of the equilibrium joint distributions, the unique equilibrium payoffs, and the unique sets of equilibrium univariate marginal distributions. Before proceeding, observe the following notational conventions which will be used throughout the appendix. For points in  $\mathbb{R}^n$ , we will use the vector notation  $\mathbf{x} = (x_1, x_2, \dots, x_n)$ . For  $a_k \leq b_k$  for all  $k = 1, 2, \dots, n$ , let  $[\mathbf{a}, \mathbf{b}]$  denote the  $n$ -box  $B = [a_1, b_1] \times [a_2, b_2] \times \dots \times [a_n, b_n]$ , the Cartesian product of  $n$  closed intervals. The vertices of the  $n$ -box  $B$  are the points  $(c_1, c_2, \dots, c_n)$  where  $c_k$  is equal to  $a_k$  or  $b_k$ . Lastly, let  $\bar{s}_i^j$  and  $\underline{s}_i^j$  denote the upper and lower bounds, respectively, for player  $i$ 's distribution of force for target  $j$ .

Given that the defender is using the distribution of force  $P_D$ , let

$$Pr \left( \max \left( \{ \iota_j^B \}_{j \in \mathcal{B}}, \{ \iota_j^W \}_{j \in \mathcal{W}} \right) = 1 \middle| P_D, \mathbf{x}_A \right) \quad (1)$$

denote the probability that with a force allocation of  $\mathbf{x}_A$  the attacker wins at least one network. Thus, the attacker's expected payoff from any pure strategy  $\mathbf{x}_A$  is

$$v_A Pr \left( \max \left( \{ \iota_j^B \}_{j \in \mathcal{B}}, \{ \iota_j^W \}_{j \in \mathcal{W}} \right) = 1 \middle| P_D, \mathbf{x}_A \right) - \sum_i x_A^i. \quad (2)$$

It will also be useful to note that the attacker's expected payoff from any distribution of force  $P_A$  is

$$v_A E_{P_A} \left[ Pr \left( \max \left( \{ \iota_j^B \}_{j \in \mathcal{B}}, \{ \iota_j^W \}_{j \in \mathcal{W}} \right) = 1 \middle| P_D, \mathbf{x}_A \right) \right] - \sum_i E_{P_A^i} [x_A^i] \quad (3)$$

where  $E_{P_A}$  denotes the expectation with respect to the joint distribution of force  $P_A$  and  $E_{P_A^i}$  denotes the expectation with respect to the univariate marginal distribution for target  $i$ , henceforth  $P_A^i$ , of the joint distribution of force  $P_A$ .

Similarly, given that the attacker is using the distribution of force  $P_A$ , let

$$Pr \left( \max \left( \{\iota_j^B\}_{j \in \mathcal{B}}, \{\iota_j^W\}_{j \in \mathcal{W}} \right) = 0 \middle| P_A, \mathbf{x}_D \right) \quad (4)$$

denote the probability that with a force allocation of  $\mathbf{x}_D$  the defender wins all of the networks in the supra-network. Thus, the defender's expected payoff from any pure strategy  $\mathbf{x}_D$  is

$$v_D Pr \left( \max \left( \{\iota_j^B\}_{j \in \mathcal{B}}, \{\iota_j^W\}_{j \in \mathcal{W}} \right) = 0 \middle| P_A, \mathbf{x}_D \right) - \sum_i x_D^i. \quad (5)$$

Lastly, the defender's expected payoff from any distribution of force  $P_D$  is

$$v_D E_{P_D} \left[ Pr \left( \max \left( \{\iota_j^B\}_{j \in \mathcal{B}}, \{\iota_j^W\}_{j \in \mathcal{W}} \right) = 0 \middle| P_A, \mathbf{x}_D \right) \right] - \sum_i E_{P_D^i} [x_D^i] \quad (6)$$

where  $E_{P_D}$  and  $E_{P_D^i}$  denote the expectation with respect to the joint distribution of force  $P_D$  and the expectation with respect to the univariate marginal distribution for target  $i$ ,  $P_D^i$ , respectively.

We begin by showing that for each target  $i$  within weakest-link (best-shot) network  $j$ , both players' distributions of force have the same upper bound, denoted  $\bar{s}_W^j$  ( $\bar{s}_B^j$ ), and a lower bound of 0 (0).

**Lemma 1.** *In any equilibrium: (i) for each  $j \in \mathcal{W}$ ,  $\bar{s}_A^i = \bar{s}_D^i = \bar{s}_W^j > 0$  and  $\underline{s}_A^i = \underline{s}_D^i = 0$  for all  $i \in N_j$ , and (ii) for each  $j \in \mathcal{B}$ ,  $\bar{s}_A^i = \bar{s}_D^i = \bar{s}_B^j > 0$  and  $\underline{s}_A^i = \underline{s}_D^i = 0$  for all  $i \in N_j$ .*

*Proof.* We begin with the proof that  $\underline{s}_A^i = \underline{s}_D^i = 0$  for all  $i$ . By way of contradiction, suppose  $\underline{s}_A^i \neq \underline{s}_D^i$ . Let  $\hat{s}^i \equiv \max\{\underline{s}_A^i, \underline{s}_D^i\}$ , and let  $l$  be the identity of the player attaining  $\hat{s}^i$  (that is  $\hat{s}^i = \underline{s}_l^i$  and  $\hat{s}^i > \underline{s}_{-l}^i$ ).

If  $\underline{s}_{-l}^i > 0$ , when player  $-l$  allocates  $\underline{s}_{-l}^i$  to target  $i$  player  $-l$  loses target  $i$  with certainty and can strictly increase his payoff by setting  $\underline{s}_{-l}^i = 0$ . It follows directly, that player  $-l$  does

not randomize over the open interval  $(0, \underline{s}^i)$ , and thus player  $-l$  must have a mass point at 0.

In the case that  $\underline{s}_{-l}^i = 0$  (where player  $-l$  does not randomize over the open interval  $(0, \underline{s}^i)$  and has a mass point at 0), we know that (i) both players cannot have a mass point at  $\underline{s}_l^i$ , (ii) player  $-l$  cannot place mass at  $\underline{s}_l^i$ , and (iii) player  $l$  can strictly increase his payoff by lowering  $\underline{s}_l^i$  to a neighborhood above 0. Thus, we conclude that  $\underline{s}_A^i = \underline{s}_D^i = 0$  for all  $i$ .

Lastly, for the proof that for each  $j \in \mathcal{W}$ ,  $\bar{s}_A^i = \bar{s}_D^i = \bar{s}_W^j > 0$  for all  $i \in N_j$ , note that if there exists a target  $i$  such that  $\bar{s}_A^i = \bar{s}_D^i = 0$ , then player  $A$  can strictly increase his payoff by allocating an arbitrarily small, but strictly positive, level of force to weakest-link target  $i$ . Similarly, for any pair  $i', i'' \in N_j$  it follows that if  $\bar{s}_A^{i'} = \bar{s}_D^{i'} < \bar{s}_A^{i''} = \bar{s}_D^{i''}$  then player  $A$  would do better by moving mass from  $\bar{s}_A^{i''}$  to  $\bar{s}_A^{i'}$ . The proof that for each  $j \in \mathcal{B}$ ,  $\bar{s}_A^i = \bar{s}_D^i = \bar{s}_B^j > 0$  for all  $i \in N_j$  follows from a similar argument.  $\square$

**Lemma 2.** *In any equilibrium  $\{P_A, P_D\}$  with the set of univariate marginal distributions  $\{P_A^i, P_D^i\}_{i=1}^n$ , for each target  $i$  neither player's univariate marginal distribution places positive mass on any point except possibly at zero.*

*Proof.* If for target  $i$ ,  $x_l^i > 0$  is such a point for player  $l$ , then player  $-l$  would either benefit from moving mass from an  $\epsilon$ -neighborhood below  $x_l^i$  to zero or to a  $\delta$ -neighborhood above  $x_l^i$ .  $\square$

**Lemma 3.** *In any equilibrium, each player's expected payoff (equations (2) and (5) for the attacker and defender respectively) is constant over the support of his joint distribution except possibly at points of discontinuity of his expected payoff function.*

*Proof.* Except for possibly at points of discontinuity of his expected payoff function, each player  $l$  must make his equilibrium expected payoff at each point in the support of his equilibrium strategy,  $P_l$ . Otherwise, player  $l$  would benefit by moving mass to the  $n$ -tuple(s) in his support with the highest expected payoff.  $\square$

**Lemma 4.** *In any equilibrium  $\{P_A, P_D\}$  with the set of univariate marginal distributions  $\{P_A^i, P_D^i\}_{i=1}^n$ , for each target  $i$  each player  $l$ 's univariate marginal distribution  $P_l^i$  randomizes continuously over the interval  $(0, \bar{s}^i]$ .*

*Proof.* Lemma 2 rules out mass points of  $P_l^i$  in the interval  $(0, \bar{s}^i]$ . To rule out gaps, by way of contradiction, suppose that there exists an equilibrium in which for some target  $i$ , player  $l$ 's univariate marginal distribution for target  $i$ ,  $P_l^i$ , is constant over the interval  $[\alpha, \beta) \subset (0, \bar{s}^i]$  and strictly increasing above  $\beta$  in its support. For this to be an equilibrium, it must be the case that  $P_{-l}^i$  is also constant over the interval  $[\alpha, \beta)$ . Otherwise, player  $-l$  could increase his payoff.

If  $P_{-l}^i(\alpha) = P_{-l}^i(\beta)$ , then for sufficiently small  $\epsilon > 0$  spending  $\beta + \epsilon$  in target  $i$  cannot be optimal for player  $l$ . Indeed, by discretely reducing his expenditure from  $\beta + \epsilon$  to  $\alpha + \epsilon$  player  $l$ 's payoff would strictly increase. Consequently, if  $P_l^i$  is constant over  $[\alpha, \beta)$  it must also be constant over  $[\alpha, \bar{s}^i]$ , a contradiction to the definition of  $\bar{s}^i$ .  $\square$

**Lemma 5.** *In any equilibrium  $\{P_A, P_D\}$ :*

- (a) *If  $\mathbf{x}_A$  is an  $n$ -tuple contained in the support of  $P_A$ , then  $\mathbf{x}_A$  allocates a strictly positive level of force to at most one network.*
- (b) *If the  $n$ -tuple  $\mathbf{x}_A$  (contained in the support of  $P_A$ ) allocates a strictly positive level of force to a weakest-link network, then one target in that weakest-link network receives a strictly positive level of force.*
- (c) *If  $\mathbf{x}_D$  is an  $n$ -tuple contained in the support of  $P_D$ , then within each best-shot network  $\mathbf{x}_D$  allocates a strictly positive level of force to at most one target in the network.*

*Proof.* We begin with the proof of part (a). By way of contradiction suppose that there exists an equilibrium  $\{P_A, P_D\}$  such that for a positive measure of points in the support of  $P_A$  at least two networks simultaneously receive strictly positive levels of force (henceforth,

simultaneously attacked). There are three cases to consider. In case (i) only best-shot networks are simultaneously attacked. In case (ii) only weakest-link networks are simultaneously attacked. Case (iii) includes all remaining configurations of simultaneous attacks.

Before moving on, we introduce some notation. Let  $\mathbf{x}_A^j$  denote the restriction of the vector  $\mathbf{x}_A$  to the set of targets contained in network  $j$  (i.e.,  $\{x_A^i\}_{i \in N_j}$ ). Denote the set of points in the support of  $P_A$  that simultaneously attack at least two networks as

$$\Omega_A \equiv \{\mathbf{x}_A \in \text{Supp}\{P_A\} \mid \mathbf{x}_A^j \neq \mathbf{0} \text{ for at least two } j \in \mathcal{B} \cup \mathcal{W}\}.$$

For each point  $\mathbf{x}_A \in \Omega_A$  let  $\mathcal{P}_{\mathbf{x}_A}(j \in \mathcal{B} \cup \mathcal{W} \mid \mathbf{x}_A^j \neq \mathbf{0})$  denote the power set of the indices of networks that player  $A$  simultaneously attacks at the point  $\mathbf{x}_A$ . Let  $\psi$  denote an arbitrary element of this power set, let  $|\psi|$  denote the cardinality of the set  $\psi$ , and let  $\mathbf{x}_A^\psi$  denote the restriction of the vector  $\mathbf{x}_A$  to the set of targets contained in the networks in  $\psi$  (i.e.,  $\{x_A^i\}_{i \in \cup_{j \in \psi} N_j}$ ). For each point  $\mathbf{x}_A \in \Omega_A$  define  $\mathcal{J}(\mathbf{x}_A) = \{j \in \mathcal{B} \cup \mathcal{W} \mid \mathbf{x}_A^j \neq \mathbf{0}\}$  as the set of the indices of networks that player  $A$  simultaneously attacks at the point  $\mathbf{x}_A$ .

If at the point  $\mathbf{x}_A \in \Omega_A$  player  $A$  simultaneously attacks two networks  $j'$  and  $j''$ , then the probability that at  $\mathbf{x}_A \in \Omega_A$  player  $A$  wins at least one network is given by Claim 1.

**Claim 1.** *If at  $\mathbf{x}_A \in \Omega_A$  player  $A$  simultaneously attacks two networks  $j'$  and  $j''$ , then the probability that player  $A$  wins at least one network is*

$$\begin{aligned} Pr \left( \max \left( \{l_j^B\}_{j \in \mathcal{B}}, \{l_j^W\}_{j \in \mathcal{W}} \right) = 1 \mid P_D, \mathbf{x}_A \right) = \\ Pr \left( l_{j'} = 1 \mid P_D, \mathbf{x}_A^{j'} \right) + Pr \left( l_{j''} = 1 \mid P_D, \mathbf{x}_A^{j''} \right) - Pr \left( l_{j'}, l_{j''} = 1 \mid P_D, \mathbf{x}_A^{j', j''} \right) \quad (7) \end{aligned}$$

Note that the third term in the second line of (7) corrects for the first two terms' multiple countings of player  $A$  winning at least one network. Next, we consider the probability that player  $A$  wins at least one network in the special case that player  $A$  simultaneously attacks

three networks.

**Claim 2.** *If at  $\mathbf{x}_A \in \Omega_A$  player A simultaneously attacks three networks  $j'$ ,  $j''$ , and  $j'''$ , then*

$$\begin{aligned}
Pr\left(\max\left(\{l_j^B\}_{j \in \mathcal{B}}, \{l_j^W\}_{j \in \mathcal{W}}\right) = 1 \middle| P_D, \mathbf{x}_A\right) = & \\
& Pr\left(l_{j'} = 1 \middle| P_D, \mathbf{x}_A^{j'}\right) + Pr\left(l_{j''} = 1 \middle| P_D, \mathbf{x}_A^{j''}\right) + Pr\left(l_{j'''} = 1 \middle| P_D, \mathbf{x}_A^{j'''}\right) \\
& - Pr\left(l_{j'}, l_{j''} = 1 \middle| P_D, \mathbf{x}_A^{j', j''}\right) - Pr\left(l_{j'}, l_{j'''} = 1 \middle| P_D, \mathbf{x}_A^{j', j'''}\right) - Pr\left(l_{j'', l_{j'''} = 1 \middle| P_D, \mathbf{x}_A^{j'', j'''}\right) \\
& + Pr\left(l_{j'', l_{j''}, l_{j'''} = 1 \middle| P_D, \mathbf{x}_A^{j'', j''', j'''}\right). \quad (8)
\end{aligned}$$

Again, note that the third and fourth lines of (8) correct for the second line's multiple countings of player A winning at least one network. Given Claims 1 and 2, a straightforward proof by induction can be used to establish that for any arbitrary point  $\mathbf{x}_A \in \Omega_A$  the probability that player A wins at least one network is given as follows.

**Claim 3.** *At an arbitrary point  $\mathbf{x}_A \in \Omega_A$  the probability that player A wins at least one network is given by*

$$\begin{aligned}
Pr\left(\max\left(\{l_j^B\}_{j \in \mathcal{B}}, \{l_j^W\}_{j \in \mathcal{W}}\right) = 1 \middle| P_D, \mathbf{x}_A\right) = & \\
& \sum_{\psi \in \mathcal{P}(j \in \mathcal{B} \cup \mathcal{W} | \mathbf{x}_A^j \neq \mathbf{0}) - \emptyset} (-1)^{(|\psi|-1)} Pr\left(l_j = 1 \forall j \in \psi \middle| P_D, \mathbf{x}_A^\psi\right). \quad (9)
\end{aligned}$$

Beginning with the proof by contradiction of case (i) of part (a) — in which simultaneous attacks occur on only best-shot networks — recall that in order to win a best-shot network player A has to allocate a strictly higher level of force to every target in the network. Thus, it is strictly suboptimal in a best-shot network  $j$  for player A to have  $\mathbf{x}_A^j \neq \mathbf{0}$  with  $x_A^i = 0$  for some  $i \in N_j$ , and, in the discussion that follows, we focus on the case in which if  $\mathbf{x}_A^j \neq \mathbf{0}$  then  $x_A^i > 0$  for all  $i \in N_j$ . For any  $\mathbf{x}_A \in \text{Supp}(P_A)$  such that  $\mathbf{x}_A^j \neq \mathbf{0}$  for some best-shot network  $j$ , the probability that player A wins every target in network  $j$ , and hence wins

network  $j$  is

$$Pr(\iota_j = 1 | P_D^{N_j}, \mathbf{x}_A^j) = P_D^{N_j}(\mathbf{x}_A^j), \quad (10)$$

where  $P_D^{N_j}$  is the  $n_j$ -variate marginal distribution for network  $j$ . For each  $\mathbf{x}_A \in \Omega_A$ , the probability that at the point  $\mathbf{x}_A \in \Omega_A$  player  $A$  wins every target in each best-shot network  $j \in \psi$  is

$$Pr\left(\iota_j = 1 \forall j \in \psi \mid P_D, \mathbf{x}_A\right) = P_D^\psi(\mathbf{x}_A^\psi) \quad (11)$$

where  $P_D^\psi$  is the  $(\sum_{j \in \psi} n_j)$ -variate marginal distribution over all of the networks  $j \in \psi$ .

In the proof that follows we will make use of a joint distribution function,  $\hat{P}_D$ , that involves the application of the Fréchet-Hoeffding upper-bound  $n$ -copula<sup>14</sup> to player  $D$ 's set of (multivariate) marginal distributions for each of the  $k$  networks,  $\{P_D^{N_j}\}_{j \in \mathcal{B} \cup \mathcal{W}}$ , under the strategy  $P_D$ . That is,  $\hat{P}_D(\mathbf{x}_A) = \min_{j \in \mathcal{B} \cup \mathcal{W}} \{P_D^{N_j}(\mathbf{x}_A^j)\}$ . Clearly this is a valid joint distribution function;<sup>15</sup> for each  $j \in \mathcal{B} \cup \mathcal{W}$  the  $n_j$ -variate marginal distribution  $P_D^{N_j}(\mathbf{x}_A^j)$  is preserved; for each  $i \in \cup_{j \in \mathcal{B} \cup \mathcal{W}} N_j$  the univariate marginal distribution  $P_D^i(x_A^i)$  is preserved; and for each  $\mathbf{x}_A \in \Omega_A$

$$\hat{P}_D^{N_{\mathcal{J}(\mathbf{x}_A)}}(\mathbf{x}_A^{\mathcal{J}(\mathbf{x}_A)}) = \min_{j \in \mathcal{J}(\mathbf{x}_A)} \{P_D^{N_j}(\mathbf{x}_A^j)\} \quad (12)$$

where  $P_D^{N_{\mathcal{J}(\mathbf{x}_A)}}$  is the  $(\sum_{j \in \mathcal{J}(\mathbf{x}_A)} n_j)$ -variate marginal distribution over all of the networks  $j \in \mathcal{J}(\mathbf{x}_A)$ . Because the expected cost of the strategy  $P_D$  — given in the second term in (6) — depends on only the set of univariate marginal distributions  $\{P_D^i\}_{i \in \cup_{j \in \mathcal{B} \cup \mathcal{W}} N_j}$ , the strategy  $\hat{P}_D(\mathbf{x}_A)$  has the same expected cost as  $P_D(\mathbf{x}_A)$ .

Inserting (10), (11), and (12) into (9) a straightforward proof by induction (beginning with (7) and (8)) yields the following result.

**Claim 4.** *If player  $D$  uses the strategy  $\hat{P}_D(\mathbf{x}_A)$ , then for each  $\mathbf{x}_A \in \Omega_A$  the probability that*

<sup>14</sup>See Nelsen (1999) and Schweizer and Sklar (1983) for more details.

<sup>15</sup>Note that for each  $j \in \mathcal{B} \cup \mathcal{W}$  the random variable  $\tilde{x}^j \equiv P_D^{N_j}(\mathbf{x}_A^j)$  is uniformly distributed on the interval  $[0, 1]$ . Thus, no compatibility issue (for details see section 3.5 of Nelsen 2006) arises in applying an  $n$ -copula to the set of multi-variate joint distributions  $\{P_D^{N_j}(\mathbf{x}_A^j)\}_{j \in \mathcal{B} \cup \mathcal{W}}$ .

player  $A$  successfully attacks at least one of the best-shot networks is

$$Pr \left( \max \left( \{\ell_j^B\}_{j \in \mathcal{B}}, \{\ell_j^W\}_{j \in \mathcal{W}} \right) = 1 \middle| \hat{P}_D, \mathbf{x}_A \right) = \max_{j \in \mathcal{B} | \mathbf{x}_A^j \neq \mathbf{0}} \{P_D^{N_j}(\mathbf{x}_A^j)\}. \quad (13)$$

Given that  $\hat{P}_D$  is the Fréchet-Hoeffding upper-bound, we know that<sup>16</sup> for any  $\mathbf{x}_A^{\mathcal{J}(\mathbf{x}_A)}$  in  $\text{dom } P_D^{N_{\mathcal{J}(\mathbf{x}_A)}}$ ,

$$P_D^{N_{\mathcal{J}(\mathbf{x}_A)}}(\mathbf{x}_A^{\mathcal{J}(\mathbf{x}_A)}) \leq \hat{P}_D^{N_{\mathcal{J}(\mathbf{x}_A)}}(\mathbf{x}_A^{\mathcal{J}(\mathbf{x}_A)}). \quad (14)$$

We now have the following result regarding  $\hat{P}_D$ .

**Claim 5.** For each  $\mathbf{x}_A \notin \Omega_A$ ,

$$Pr \left( \max \left( \{\ell_j^B\}_{j \in \mathcal{B}}, \{\ell_j^W\}_{j \in \mathcal{W}} \right) = 1 \middle| P_D, \mathbf{x}_A \right) = Pr \left( \max \left( \{\ell_j^B\}_{j \in \mathcal{B}}, \{\ell_j^W\}_{j \in \mathcal{W}} \right) = 1 \middle| \hat{P}_D, \mathbf{x}_A \right).$$

For each  $\mathbf{x}_A \in \Omega_A$ ,

$$Pr \left( \max \left( \{\ell_j^B\}_{j \in \mathcal{B}}, \{\ell_j^W\}_{j \in \mathcal{W}} \right) = 1 \middle| P_D, \mathbf{x}_A \right) \geq Pr \left( \max \left( \{\ell_j^B\}_{j \in \mathcal{B}}, \{\ell_j^W\}_{j \in \mathcal{W}} \right) = 1 \middle| \hat{P}_D, \mathbf{x}_A \right)$$

where if  $P_D^{N_{\mathcal{J}(\mathbf{x}_A)}}(\mathbf{x}_A^{\mathcal{J}(\mathbf{x}_A)}) \neq \hat{P}_D^{N_{\mathcal{J}(\mathbf{x}_A)}}(\mathbf{x}_A^{\mathcal{J}(\mathbf{x}_A)})$  then this inequality is strict.

If  $\mathbf{x}_A \notin \Omega_A$ , then player  $A$  attacks at most one network and the first part of the claim follows directly. For the second part of the claim, we begin with the case that player  $A$  attacks two networks  $j'$  and  $j''$ . Suppose, without loss of generality, that  $P_D^{N_{j'}}(\mathbf{x}_A^{j'}) \geq P_D^{N_{j''}}(\mathbf{x}_A^{j''})$ . Inserting (10) into Claim 1, the second part of Claim 5 follows from Claim 4 combined with (14). For the case that player  $A$  attacks more than two networks, there exists a  $j' \in \mathcal{J}(\mathbf{x}_A)$  such that  $P_D^{N_{j'}}(\mathbf{x}_A^{j'}) \geq P_D^{N_j}(\mathbf{x}_A^j)$  for all  $j \in \mathcal{J}(\mathbf{x}_A)$ . Because player  $A$  cannot strictly increase his probability of winning at least one network by modifying  $\mathbf{x}_A$  so that  $\mathbf{x}_A^j = \mathbf{0}$  for all  $j \neq j', j''$  where  $j'' \in \mathcal{J}(\mathbf{x}_A)$  such that  $j'' \neq j'$  (i.e. deviate to attacking only best-shot

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<sup>16</sup>This follows directly from Lemma 6.1.7 (p.80) of Schweizer and Sklar (1983).



networks  $j'$  and  $j''$ ) and we know that the second part of Claim 5 applies in the case that player  $A$  only attacks two networks  $j'$  and  $j''$ , the second part of Claim 5 extends directly to the case that player  $A$  attacks more than two networks.<sup>17</sup>

Returning to the proof of part (a), if for almost every  $\mathbf{x}_A \in \Omega_A$ ,  $P_D^{N_{\mathcal{J}(\mathbf{x}_A)}}(\mathbf{x}_A^{\mathcal{J}(\mathbf{x}_A)}) = \hat{P}_D^{N_{\mathcal{J}(\mathbf{x}_A)}}(\mathbf{x}_A^{\mathcal{J}(\mathbf{x}_A)})$ , then from (2) and Claim 4 player  $A$  can strictly increase his payoff by modifying each subset of  $\Omega_A$  that has positive measure by choosing, at each  $\mathbf{x}_A$  in such subsets, a network  $j$  such that  $P_D^{N_j}(\mathbf{x}_A^j) \geq P_D^{N_{j'}}(\mathbf{x}_A^{j'})$  for all  $j' \in \mathcal{J}(\mathbf{x}_A)$  and setting  $\mathbf{x}_A^{j'} = \mathbf{0}$  for all  $j' \neq j$ . A contradiction to the assumption that  $\{P_A, P_D\}$  is an equilibrium. Conversely, Claim 5 implies that if there exists a subset of  $\mathbf{x}_A \in \Omega_A$  with positive measure such that  $P_D^{N_{\mathcal{J}(\mathbf{x}_A)}}(\mathbf{x}_A^{\mathcal{J}(\mathbf{x}_A)}) \neq \hat{P}_D^{N_{\mathcal{J}(\mathbf{x}_A)}}(\mathbf{x}_A^{\mathcal{J}(\mathbf{x}_A)})$ , then there exists a strictly payoff increasing deviation for player  $D$ . A contradiction to the assumption that  $\{P_A, P_D\}$  is an equilibrium. This completes the proof of part (i) of the proof of (a).

Before moving on to cases (ii) and (iii) in the proof of part (a), note that the argument given above can be used to establish part (b) of Lemma 5 (i.e., within each weakest-link network player  $A$  attacks at most one target). In particular, at target  $i$  in weakest-link network  $j$  let  $\iota_{j,i} = 1$  if  $x_A^i > x_D^i$  and  $\iota_{j,i} = 0$  otherwise. Letting  $\iota_j \equiv \max_{i \in N_j} \{\iota_{j,i}\}$ , the probability that player  $A$  wins weakest-link network  $j$  is given by  $Pr(\iota_j = 1 | P_D^{N_j}, \mathbf{x}_A)$ . Then by choosing  $P_D^{N_j}(\mathbf{x}_A^j) = \min_{i \in N_j} \{P_D^i(x_A^i)\}$ , player  $D$ 's univariate marginals and hence the expected cost remain the same, the correlation of player  $D$ 's allocation of force among the networks is unaffected, and the correlation of player  $D$ 's allocation of force among the targets in weakest-link network  $j$  renders all simultaneous attacks among the targets in weakest-link network  $j$  equivalent to an attack on only  $\bar{i} = \arg \max_{i \in N_j} \{P_D^i(x_A^i)\}$ . Thus, in equilibrium the attacker allocates a strictly positive level of force to at most one target in each weakest-link

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<sup>17</sup>For the strict inequality, note that by assumption  $P_D$  is an equilibrium strategy and  $\mathbf{x}_A \in \Omega_A$  is a point in  $\text{sup } P_A$ , also an equilibrium strategy. Thus, the deviation to attacking only best-shot networks  $j'$  and  $j''$  cannot be payoff increasing, i.e. at any point  $\mathbf{x}_A$  at which more than two best-shot networks are attacked the probability that the attacker wins at least one network must be strictly greater than at the cost-decreasing deviation from  $\mathbf{x}_A$  in which  $\mathbf{x}_A^j = \mathbf{0}$  for all  $j \neq j', j''$  where  $j'' \in \mathcal{J}(\mathbf{x}_A)$  such that  $j'' \neq j'$ .

network. The proof for part (c) of Lemma 5 follows from a symmetric argument.

Returning to the proof of case (ii) of part (a) of Lemma 5, from part (b) of Lemma 5, player  $A$  attacks at most one target in any weakest-link network, and the probability that player  $A$  wins weakest-link network  $j$  with an allocation of  $x_A^{i'} > 0$  and  $x_A^i = 0 \forall i \in N_j - i'$ , is

$$Pr(\iota_j = 1 | P_D^{N_j}, \mathbf{x}_A^j) = P_D^{i'}(x_A^{i'}). \quad (15)$$

If player  $D$  uses the strategy  $\hat{P}_D$ , then for each  $\psi \in \mathcal{P}(j \in \mathcal{W} | \mathbf{x}_A^j \neq \mathbf{0}) \setminus \{\emptyset\}$  it follows from (15) that the probability that player  $A$  wins every weakest-link network  $j \in \psi$  is

$$Pr(\iota_j = 1 \forall j \in \psi | \hat{P}_D, \mathbf{x}_A) = \min_{i \in \cup_{j \in \psi} N_j | x_A^i > 0} \{P_D^i(x_A^i)\}. \quad (16)$$

Inserting (15) and (16) into (9) a straightforward proof by induction shows that for each point  $\mathbf{x}_A \in \Omega_A$  satisfying the conditions of case (ii)

$$Pr\left(\max\left(\{\iota_j^B\}_{j \in \mathcal{B}}, \{\iota_j^W\}_{j \in \mathcal{W}}\right) = 1 \mid \hat{P}_D, \mathbf{x}_A\right) = \max_{i \in \cup_{j \in \mathcal{W}} N_j | x_A^i > 0} \{P_D^i(x_A^i)\}. \quad (17)$$

From (17) it is clear that an argument similar to that used to establish case (i) applies. This completes the proof of case (ii). The proof of case (iii) follows along similar lines.  $\square$

**Lemma 6.** *In any equilibrium,  $\bar{s}_W^j = \bar{s}_W^{j'} \equiv \bar{s}_W, \forall j', j'' \in \mathcal{W}$ .*

*Proof.* Following from Lemmas 1, 2 and 5, in the support of any equilibrium strategy, when player  $A$  allocates  $\bar{s}_W^{j'}$  to a single target in network  $j'$  the force allocated to each of the remaining targets is 0, player  $A$  wins network  $j'$  with certainty, and player  $A$ 's expected payoff is  $v_A - \bar{s}_W^{j'}$ .

From Lemma 3, player  $A$ 's expected payoff is constant across all points in the support of  $P_A$  except for points of discontinuity of the expected payoff function. Thus, from Lemma 4  $\forall j', j'' \in \mathcal{W}, v_A - \bar{s}_W^{j'} = v_A - \bar{s}_W^{j''}$ , or equivalently  $\bar{s}_W^{j'} = \bar{s}_W^{j''} \equiv \bar{s}_W$ .  $\square$

**Lemma 7.** *In any equilibrium  $\{P_A, P_D\}$ , there exists a  $k_A \geq 0$  such that for any best-shot network  $j$  and every  $n_j$ -tuple  $\mathbf{x}_A^j \in [0, \bar{s}_B^j]^{n_j}$ ,  $P_D^{N_j}(\mathbf{x}_A^j) = \frac{k_A}{v_A} + \frac{\sum_{i \in N_j} x_A^i}{v_A}$ .*

*Proof.* From Lemma 5 part (c) in the support of any optimal strategy player  $D$  allocates a strictly positive level of force to at most one target in network  $j$ , and thus the support of player  $D$ 's  $n_j$ -variate marginal distribution for network  $j$ ,  $P_D^{N_j}$ , is located on the axes in  $\mathbb{R}_+^{n_j}$ . Combining this with Lemma 4 — each of player  $D$ 's univariate marginals randomizes continuously over the interval  $(0, \bar{s}_B^j]$  — it follows that there are no mass points in the support of player  $D$ 's  $n_j$ -variate marginal distribution for network  $j$ ,  $P_D^{N_j}$ , except for possibly at the origin in  $\mathbb{R}_+^{n_j}$ .

Combining Lemma 5 part (a) — in the support of any equilibrium strategy player  $A$  attacks at most one network — with Lemmas 3 and 4, it follows that for each best-shot network  $j$  there exists a  $k_A \geq 0$  such that for each  $\mathbf{x}_A$  in the support of  $P_A$  in which  $\mathbf{x}_A^j \in (0, \bar{s}_B^j]^{n_j}$

$$Pr\left(\iota_j^B = 1 \mid P_D^{N_j}, \mathbf{x}_A\right) = P_D^{N_j}(\mathbf{x}_A^j) = \frac{k_A}{v_A} + \frac{\sum_{i \in N_j} x_A^i}{v_A}. \quad (18)$$

Moreover, from the definition of  $\iota_j^B$  it is clear that for each  $\mathbf{x}_A$  in the support of any equilibrium strategy  $P_A$  such that  $\mathbf{x}_A^j \neq \mathbf{0}$ , it must be that  $\mathbf{x}_A^j \in (0, \bar{s}_B^j]^{n_j}$ . Otherwise, player  $A$  could increase his payoff by setting  $\mathbf{x}_A^j = \mathbf{0}$ .

The proof that follows shows that the second equality in equation (18) holds not only for each  $\mathbf{x}_A$  in the support of  $P_A$  such that  $\mathbf{x}_A^j \neq \mathbf{0}$ , but for all  $n_j$ -tuples  $\mathbf{x}^j \in [0, \bar{s}_B^j]^{n_j}$ .

Consider an arbitrary point  $\mathbf{x}_A \in \text{Supp}(P_A)$  in which  $x_A^{i'} \in (0, \bar{s}_B^j)$  for  $i' \in N_j$ . Because  $\mathbf{x}_A \in \text{Supp}(P_A)$  and  $\mathbf{x}_A^j \neq \mathbf{0}$ , we know that  $\mathbf{x}_A^j \in (0, \bar{s}_B^j]^{n_j}$ , and thus, equation (18) applies. From Lemma 4, there exists an  $\epsilon^{i'} > 0$  such that  $(x_A^{i'} + \epsilon^{i'}) \in (0, \bar{s}_B^j]$ . Furthermore, there exists a point  $\tilde{\mathbf{x}}_A \in \text{Supp}(P_A)$  such that  $\tilde{x}_A^{i'} = (x_A^{i'} + \epsilon^{i'})$ . Similarly, for each  $i \in N_j$  such that  $i \neq i'$  define  $\epsilon^i$  as  $\epsilon^i = \tilde{x}_A^i - x_A^i$ .

Because from Lemma 5 part (a) player  $A$  attacks at most one network and in both  $\mathbf{x}_A$

and  $\tilde{\mathbf{x}}_A$  player  $A$  attacks network  $j$ , we know that for each  $i \notin N_j$ ,  $\tilde{x}_A^i = x_A^i = 0$ , and we can restrict our focus to player  $D$ 's  $n_j$ -variate marginal distribution for best-shot network  $j$ ,  $P_D^{N_j}$ . Recall that for any  $\mathbf{x}^j \in \mathbb{R}_+^{n_j}$ ,  $P_D^{N_j}(\mathbf{x}^j)$  is equal to the  $P_D^{N_j}$ -volume of the  $n_j$ -box  $[\mathbf{0}, \mathbf{x}^j]$ .

Let  $\Delta_{x_A^i}^{\tilde{x}_A^i} P_D^{N_j}(\mathbf{x}^j)$  denote the first-order differences of the function  $P_D^{N_j}$  as follows:

$$\Delta_{x_A^i}^{\tilde{x}_A^i} P_D^{N_j}(\mathbf{x}^j) = P_D^{N_j}(x^1, \dots, x^{i-1}, \tilde{x}_A^i, x^{i+1}, \dots, x^{n_j}) - P_D^{N_j}(x^1, \dots, x^{i-1}, x_A^i, x^{i+1}, \dots, x^{n_j}). \quad (19)$$

Because the support of  $P_D^{N_j}$  is located on the axes in  $\mathbb{R}_+^{n_j}$ , the expression  $\Delta_{x_A^i}^{\tilde{x}_A^i} P_D^{N_j}(\mathbf{x}_A^j)$  is the measure of the support of  $P_D^{N_j}$  over the interval  $(x_A^i, \tilde{x}_A^i)$  on the  $i$ th axis.<sup>18</sup> Note that the difference in (19) involves one point in the support of  $P_A$ ,  $(x^1, \dots, x^{i-1}, x_A^i, x^{i+1}, \dots, x^{n_j})$ , and one point,  $(x^1, \dots, x^{i-1}, \tilde{x}_A^i, x^{i+1}, \dots, x^{n_j}) \in (0, \bar{s}_B^j]^{n_j}$ , that may or may not be in the support of  $P_A$ . Because the expected payoff from the  $n_j$ -tuple  $(x^1, \dots, x^{i-1}, \tilde{x}_A^i, x^{i+1}, \dots, x^{n_j})$  must be less than or equal to the equilibrium expected payoff and from Lemma 4 the first equality in equation (18) holds at this point we know that

$$\Delta_{x_A^i}^{\tilde{x}_A^i} P_D^{N_j}(\mathbf{x}_A^j) \leq \frac{\epsilon^i}{v_A}. \quad (20)$$

Because the support of  $P_D^{N_j}$  is located on the axes in  $\mathbb{R}_+^{n_j}$ , we also know that

$$P_D^{N_j}(\tilde{\mathbf{x}}_A^j) = P_D^{N_j}(\mathbf{x}_A^j) + \sum_{i \in N_j} \Delta_{x_A^i}^{\tilde{x}_A^i} P_D^{N_j}(\mathbf{x}_A^j). \quad (21)$$

That is, the  $P_D^{N_j}$ -volume of the  $n_j$ -box  $[\mathbf{0}, \tilde{\mathbf{x}}_A^j]$  is equal to the  $P_D^{N_j}$ -volume of the  $n_j$ -box  $[\mathbf{0}, \mathbf{x}_A^j]$  plus the measure of the support of  $P_D^{N_j}$  over the interval  $(x_A^i, \tilde{x}_A^i)$  on each of the  $i \in N_j$  axes, where the caveat in footnote 18 applies.

<sup>18</sup>This interval is for the case that  $x_A^i \leq \tilde{x}_A^i$ , or equivalently  $\epsilon^i \geq 0$ , for all  $i \in N_j$ . If  $x_A^i > \tilde{x}_A^i$  for one or more  $i \in N_j$ , then  $\Delta_{x_A^i}^{\tilde{x}_A^i} P_D^{N_j}(\mathbf{x}_A^j)$  should be replaced with  $\Delta_{\min\{x_A^i, \tilde{x}_A^i\}}^{\max\{x_A^i, \tilde{x}_A^i\}} P_D^{N_j}(\mathbf{x}_A^j)$  and the relevant interval is  $(\min\{x_A^i, \tilde{x}_A^i\}, \max\{x_A^i, \tilde{x}_A^i\})$ .

Because both  $\mathbf{x}_A$  and  $\tilde{\mathbf{x}}_A$  are contained in the support of  $P_A$  and  $\mathbf{x}_A, \tilde{\mathbf{x}}_A \in (0, \bar{s}_B^j]^{n_j}$  it follows from equation (18), Lemma 1, and Lemma 2 that

$$P_D^{N_j}(\tilde{\mathbf{x}}_A^j) - P_D^{N_j}(\mathbf{x}_A^j) = \sum_{i \in N_j} \frac{\epsilon^i}{v_A} \quad (22)$$

Combining equations (21) and (22) it follows that for each  $i \in N_j$  equation (20) holds with equality. That is the measure of the support of  $P_D^{N_j}$  over the interval  $(x_A^i, \tilde{x}_A^i)$  on the  $i$ th axis is equal to  $\epsilon^i/v_A$ .

Given that the points  $\mathbf{x}_A$  and  $\tilde{\mathbf{x}}_A$  were arbitrarily chosen from the support of  $P_A$  and that there are no mass points in the support of player  $D$ 's  $n_j$ -variate marginal distribution for network  $j$ ,  $P_D^{N_j}$ , except for possibly at the origin, it follows directly that the measure of the support of  $P_D^{N_j}$  over any interval  $[a, b] \subset (0, \bar{s}_B^j]$  on the  $i$ th axis is equal to  $(b - a)/v_A$ . Furthermore, player  $D$  must place a mass point of size  $k_A/v_A$  at the point  $\mathbf{x}^j = \mathbf{0}$ , and from (18), Lemma 1, and Lemma 2,  $k_A = v_A - n_j \bar{s}_B^j \geq 0$ . This concludes the proof of Lemma 7.  $\square$

**Lemma 8.** *In any equilibrium,  $\bar{s}_W = n_j \bar{s}_B^j, \forall j \in \mathcal{B}$ .*

*Proof.* From the combination of Lemma 3, Lemma 4, Lemma 5 parts (a) and (b) and Lemma 6, for an attack of  $x_A^i \in (0, \bar{s}_W]$  on any weakest-link target  $i$  player  $A$ 's expected payoff is  $v_A - \bar{s}_W$ . Conversely, from Lemma 7 it follows that within any best-shot network  $j$  player  $A$ 's expected payoff is constant not only for those points in the support of  $P_A$  which attack network  $j$ , but for all  $n_j$ -tuples  $\mathbf{x}_A^j \in (0, \bar{s}_B^j]^{n_j}$ . If we consider the  $n_j$ -tuple consisting of  $\bar{s}_B^j$  for each of the  $n_j$  elements, then we see that player  $A$ 's expected payoff from any attack on a best-shot network  $j$  is  $v_A - n_j \bar{s}_B^j$ .

From Lemma 3, player  $A$ 's expected payoff is constant across all points in the support of  $P_A$ , except possibly at points of discontinuity of the expected payoff function. Thus,  $\forall j \in \mathcal{B}$ ,  $v_A - \bar{s}_W = v_A - n_j \bar{s}_B^j$  or equivalently  $\bar{s}_W = n_j \bar{s}_B^j$ .  $\square$

**Lemma 9.** *In any equilibrium,  $\bar{s}_W = \min\{v_A, v_D/[\sum_{j \in \mathcal{W}} n_j + \sum_{j \in \mathcal{B}} (1/n_j)]\}$ .*

*Proof.* If player  $D$  allocates: (i)  $\bar{s}_W$  to each target in each weakest-link network, (ii)  $\bar{s}_B^j$  to exactly one target in each best-shot network  $j$ , and (iii) 0 to each of the remaining targets in the best-shot networks, then from Lemmas 4, 6, and 8 player  $D$  wins all networks with certainty and has an expected payoff of  $v_D - \sum_{j \in \mathcal{W}} n_j \bar{s}_W + \sum_{j \in \mathcal{B}} (\bar{s}_W/n_j)$ . Similarly, if player  $A$  allocates  $\bar{s}_W$  to a single weakest-link target, then from Lemmas 4 and 6, player  $A$  wins the weakest-link network containing that target with certainty, and player  $A$ 's expected payoff is  $v_A - \bar{s}_W$ .

If  $v_D - \bar{s}_W[\sum_{j \in \mathcal{W}} n_j + \sum_{j \in \mathcal{B}} (1/n_j)] > 0$ , then in any equilibrium  $\{P_A, P_D\}$  player  $D$  must necessarily have a strictly positive expected payoff. As a result, for each  $\mathbf{x}_D \in \text{Supp}\{P_D\}$ , except for possibly at points of discontinuity of his expected payoff function, player  $D$  must simultaneously win all of the networks with a probability that is bounded away from zero. This, combined with part (a) of Lemma 5, Lemma 7, and the fact that in equilibrium at most one player abstains from allocating strictly positive forces to a network with positive probability, implies that in each best-shot network  $j$  player  $D$ 's mixed strategy does not place an atom on the  $n_j$ -tuple  $\mathbf{x}_D^j = \mathbf{0}$ . Recalling from the proof of Lemma 7 that in each best-shot network  $j$  player  $D$  places an atom of size  $(v_A - n_j \bar{s}_B^j)/v_A$  on the  $n_j$ -tuple  $\mathbf{x}_D^j = \mathbf{0}$ , it follows from Lemma 8 that  $v_A - \bar{s}_W = 0$ .

Next, note that if  $v_A - \bar{s}_W > 0$ , then in any equilibrium  $\{P_A, P_D\}$  player  $A$  must necessarily have a strictly positive expected payoff, and a similar argument establishes that in each best-shot network  $j$  player  $D$ 's mixed strategy *does* place an atom on the  $n_j$ -tuple  $\mathbf{x}_D^j = \mathbf{0}$ . But, if with strictly positive probability, player  $D$  abstains from allocating a strictly positive level of force to best-shot network  $j$ , then player  $D$ 's expected payoff is necessarily 0 and  $v_D - \bar{s}_W[\sum_{j \in \mathcal{W}} n_j + \sum_{j \in \mathcal{B}} (1/n_j)] \leq 0$ . To conclude the proof, since player  $D$  would never choose to set  $\bar{s}_W$  such that  $v_D - \bar{s}_W[\sum_{j \in \mathcal{W}} n_j + \sum_{j \in \mathcal{B}} (1/n_j)] < 0$ , player  $A$  has no incentive to choose a strategy with such a  $\bar{s}_W$ . It follows that,  $\bar{s}_W = \min\{v_A, v_D/[\sum_{j \in \mathcal{W}} n_j + \sum_{j \in \mathcal{B}} (1/n_j)]\}$ .  $\square$

**Lemma 10.** *There exists a unique set of equilibrium univariate marginal distributions  $\{P_A^i, P_D^i\}_{i=1}^n$ .*

*Proof.* This proof is for the uniqueness of player  $D$ 's set of univariate marginal distributions. The proof for player  $A$  is analogous. For each best-shot network  $j \in \mathcal{B}$ , Lemmas 7 and 8 show that for any  $\mathbf{x}_A^j \in [0, \bar{s}_B^j]^{n_j}$ ,  $P_D^{N_j}(\mathbf{x}_A^j) = \frac{v_A - \bar{s}_W}{v_A} + \frac{\sum_{i \in N_j} x_A^i}{v_A}$ , where from Lemma 9  $\bar{s}_W = \min\{v_A, v_D / [\sum_{j \in \mathcal{W}} n_j + \sum_{j \in \mathcal{B}} (1/n_j)]\}$  and from Lemma 8  $\bar{s}_B^j = \frac{\bar{s}_W}{n_j}$ . Thus, in each best-shot network  $j$  player  $D$ 's unique univariate marginal distributions follow from player  $D$ 's unique  $n_j$ -variate marginal distribution for network  $j$ .

From Lemma 5 parts (a) and (b), player  $A$  attacks at most one target in one weakest-link network. From Lemmas 2, 3, and 4 it follows that for each target  $i$  in each weakest-link network  $j \in \mathcal{W}$ ,

$$v_A P_D^i(x_A^i) - x_A^i = v_A - \bar{s}_W$$

for  $x_A^i \in (0, \bar{s}_W]$ . Thus, player  $D$ 's univariate marginal distributions are uniquely determined in each weakest-link network.  $\square$

Next, note that because success for player  $D$  involves simultaneously defending all networks from attack and that for each network at most one player abstains from allocating a positive level of force to the network, it follows that if with positive probability player  $D$  abstains from allocating strictly positive forces to any network then with positive probability player  $D$  optimally abstains from allocating strictly positive forces to all networks. Otherwise, player  $D$  could increase his expected payoff at such points by allocating zero forces to all networks. Combining this fact with Lemma 10, the next two lemmas follow directly. Recall that  $\alpha = v_D / (v_A [\sum_{j \in \mathcal{W}} n_j + \sum_{j \in \mathcal{B}} \frac{1}{n_j}])$ .

**Lemma 11.** *If  $\alpha \geq 1$ , then in any equilibrium: (i) player  $A$  places mass  $1 - (1/\alpha)$  at the origin, (ii) player  $A$ 's expected payoff is 0, (iii) player  $D$  does not place positive mass at the origin, and (iv) player  $D$ 's expected payoff is  $v_D - (v_D/\alpha)$ .*

**Lemma 12.** *If  $\alpha < 1$ , then in any equilibrium: (i) player D places mass  $1 - \alpha$  at the origin, (ii) player D's expected payoff is 0, (iii) player A does not place positive mass at the origin, and (iv) player A's expected payoff is  $v_A - v_A\alpha$ .*



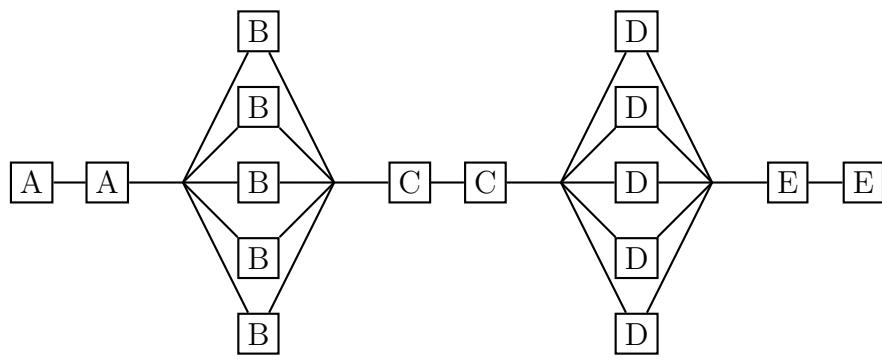
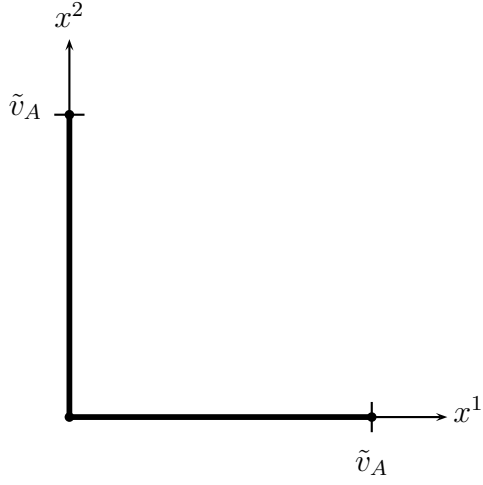
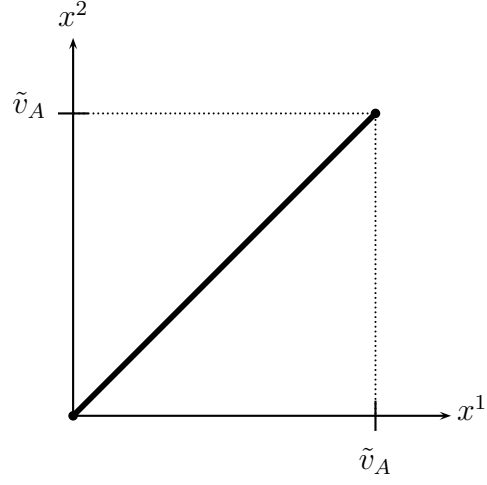


Figure 1: Example Supra-Network with Five Networks (A, B, C, D, and E)

One weakest-link network with two targets ( $i = 1, 2$ )

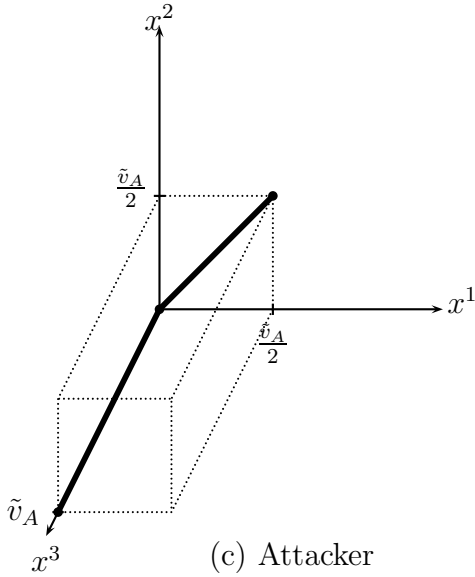


(a) Attacker

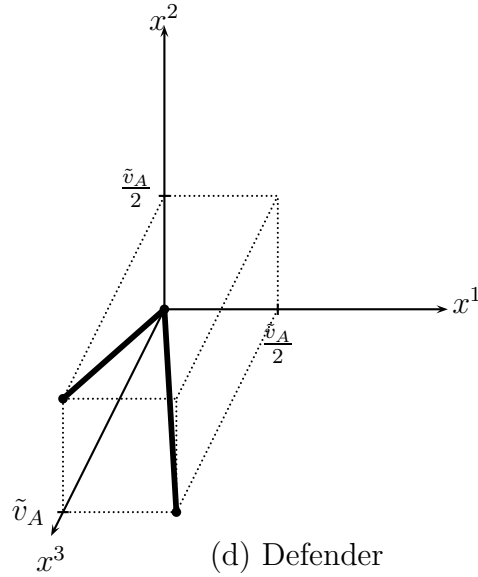


(b) Defender

One best-shot network with two targets ( $i = 1, 2$ ) and one weakest-link network with one target ( $i = 3$ )



(c) Attacker



(d) Defender

Figure 2: Supports of the equilibrium joint distributions stated in Theorem 1 ( $\tilde{v}_A = \min\{\alpha v_A, v_A\}$ ).