When Information Improves Information Security (short paper) ⋆

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Abstract. This paper presents a formal, quantitative evaluation of the impact of bounded-rational security decision-making in the presence of limited information availability and externalities. We investigate a mixed economy of an individual rational expert and several naïve near-sighted agents. We further model three canonical types of negative externalities (weakest-link, best shot and total effort), and study the impact of two information regimes on the threat level agents are facing.

Key words: Game Theory, Economics of Security, Bounded Rationality, Information

1 Introduction

Users frequently fail to deploy, or upgrade security technologies, or to carefully preserve and backup their valuable data [10, 12], which leads to considerable monetary losses to both individuals and corporations every year. A partial interpretation of this state of affairs is that *negative externalities* impede end-users' investments in security technologies [11, 14]. Negative network externalities occur when the benefit derived from adopting a technology depend on the actions of others as is frequently the case in the context of network security. For example, users who open and respond to unsolicited advertisements increase the load of spam for all participants in the network, including participants who are making the effort to adopt secure practices. Similarly, choosing a weak password for a corporate VPN system can facilitate compromises of many user accounts, possibly including those of individuals with strong passwords if trust relationships inside the VPN exist.

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In other words, a rational user facing negative externalities could make the decision *not* to invest in security primitives given that their personal investment may only marginally matter if other users are adopting insecure practices, or if the perceived cost of a security breach significantly exceeds the cost of investing in security [9].

In prior work, we addressed different canonical types of interdependencies, but we focused our analysis on users capable of gathering all relevant information and correctly understanding all implications of interconnectedness [4, 5]. This paper extends our prior analysis by relaxing several restrictive assumptions on users' rationality and information availability.

First, we anticipate the vast majority of users to be *non-expert*, and to apply approximate decision-rules that fail to accurately appreciate the impact of their decisions on others [1]. In particular, in this paper, we assume non-expert users to conduct a simple self-centered cost-benefit analysis, and to neglect externalities. Such users would secure their system only if the vulnerabilities being exploited can cause significant harm or a direct annoyance to them (e.g., their machines become completely unusable), but would not act when they cannot perceive or understand the effects of their insecure behavior (e.g., when their machine is used as a relay to send moderate amounts of spam to third parties). In contrast, an advanced, or expert user fully comprehends to which extent her and others' security choices affect the network as a whole, and responds rationally.

Second, we address how the security choices by users are mediated by the information available on the severity of the threats the network faces. We assume that each individual faces a randomly drawn probability of being subject to a direct attack. Indeed in practice, different targets, even if they are part of a same network, are not all equally attractive to an attacker: a computer containing payroll information is, for instance, considerably more valuable than an old "boat anchor" sitting under an intern's desk. Likewise, a machine may be more attractive than another due to looser restrictions in the access policies to the physical facility where the machine is located.

As an initial step, we study the strategic optimization behavior from the perspective of a sophisticated user in an economy of inexperienced users, using three canonical security games that account for externalities [4]. This approach results in a decision-theoretic model [2, 3, 13]. We present the mathematical formulation and analysis methodology in the following section which is based on our recent work focusing exclusively on the weakest-link externality [6].

2 Model and Analysis

Basic Model: Consider a game in which each of N network users is responsible for choosing security investments for their individual node. Each player begins the game with an initial endowment M, and suffers a maximum loss of L if a security breach occurs. The risk of a security breach is determined by an exogenous probability $p_i \in [0, 1]$, which for this paper we assume to be uniformly distributed. Security risks can be mitigated in two distinct ways. We denote by *protection* those security investment strategies which benefit the public network (such as installing antivirus software or firewalls), and we denote by *self-insurance* those strategies which benefit only the contributing user (such as keeping private data backups) [4]. The cost of full protection investment is de-

noted b and the cost of full self-insurance is denoted c. Each player chooses a protection investment level $e_i \in [0, 1]$ and a self-insurance investment level $s_i \in [0, 1]$. The manner in which protection strategies jointly affect players in the network is determined by an aggregate protection function $H(e_1, \ldots, e_N)$, of which we will consider three types: weakest link ($H(e_1, \ldots, e_n) = \min_j e_j$), best shot ($H(e_1, \ldots, e_n) = \max_j e_j$), and total effort ($H(e_1, \ldots, e_N) = \frac{1}{N} \sum_j e_j$). The utility for player i is given by

$$U(i) = M - p_i L(1 - H(e_1, \ldots, e_N))(1 - s_i) - be_i - cs_i.$$

Bounded rationality and limited Information: We consider distinct approaches to relax assumptions on user rationality and information availability.

First, we distinguish users based on their treatment of network interdependencies. We say a player is *naïve* if she does not take network interdependency into account in her decisions, i.e., she operates under the assumption that $H(e_1, \ldots, e_N) = e_i$. Whereas a player is of the type *expert* if she correctly perceives and understands the interdependent nature of the game. That is, she properly considers the role of H into her payoff function.

Second, we distinguish between the level of information users have about other's risks. We say that a player has *complete information* if she knows all the risk factors and costs associated to the other players. In contrast, a player has *incomplete information* if she knows her own costs and risks but not the risks of other players. Clearly, a naïve player does not use the external risk information (because she is not aware of its effects), but an expert player does. To provide a decision framework for an expert with limited information, we assume that the distribution on risk parameters is known to all players. Thus, an expert with limited information can still conduct an expected cost-benefit analysis to make a strategic decision. This setup allows us to study the extent to which the complete information is beneficial to the players and to the network.

Analysis methodology: A thorough discussion of our analysis approach can be found in our technical report [8] and in our in-depth discussion of the weakest-link externality [6]. Here we summarize the overall approach.

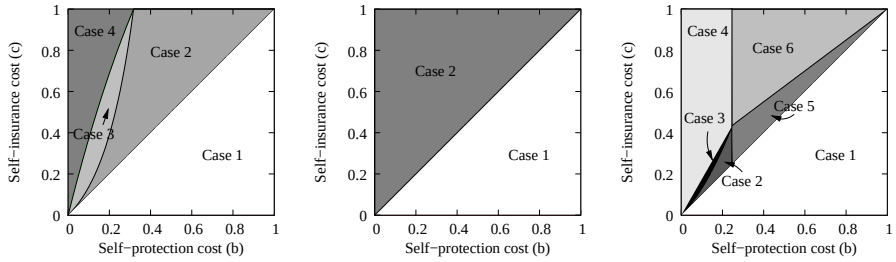
We have three types of players: naïve players, experts with incomplete information, and experts with complete information. We also have three types of network interdependencies: weakest link, best shot, and total effort. Fixing the player type, the interdependency type, and the values of all known parameters, we begin by computing an optimal strategy for the given player, and her expected payoff as a result of playing that strategy. These computations often require us to consider selected parameter orientations as separate cases, but there are a small number of separate cases (at most 6) for each game, and the expected payoff functions can be recorded neatly in tables. Due to space constraints in this paper we have omitted these tables; but they, together with all accompanying derivations may be found in our technical report [8].

The tables show an expected payoff for each type of player under the different interdependency scenarios subdivided by the distinctive parameter cases. The payoff functions involve five free variables and it remains to distill the information for further interpretive analysis. To accomplish this, we fix the parameters related to the initial endowment, M, and the total maximum loss, L, and we construct graphs to show how the expected payoffs for each player relate to the cost of protection, b, the cost of self-insurance, c, and the number of players, N.

3 Results

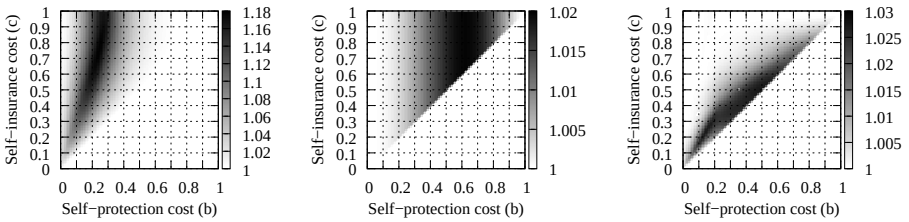
3.1 Strategies and payoffs

In this section, we highlight two results from our study. A more thorough discussion can be found in the technical report [8].



(a) Weakest link (b) Best shot (c) Total effort

Fig. 1. Strategy boundaries in the incomplete information scenario for the expert player as a function of protection and self-insurance costs. (Here we have fixed the number of players N at 4, and we have fixed the initial endowment M and the potential loss L at a unit value of 1. For the relevant analytic results used to construct these graphs, please refer to the technical report [8].



(a) Weakest link (b) Best shot (c) Total effort

Fig. 2. Heat plots showing the extent of payoff discrepancy between the expert with complete information and the expert with incomplete information as a function of protection and self-insurance costs. (As in Figure 1 we have fixed the number of players N at 4, and we have fixed the initial endowment M and the potential loss L at a unit value of 1.) For the relevant analytic results used to construct these graphs, please refer to the technical report [8].

Our first result is that the range of security parameters conducive to an environment in which limited information plays a significant role is somewhat restricted, and becomes more restricted as the number of players increases. Consider the three graphs in Figure 1. These graphs show dividing lines between various dominant strategies as function of the two types of investment costs – protection and self-insurance. Comparing these to the graphs in Figure 2, the direct relationship is clear between the parameter

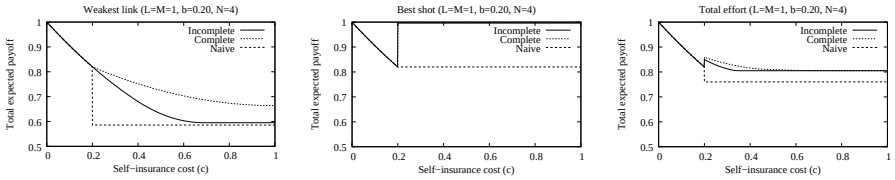
conditions that determine certain dominant strategies and the parameter conditions under which additional information has an effect on an expert player's payoff. From these graphs we can tell that information plays a substantial role in the smaller-sized cases, but in the other cases, the additional information has little to no effect. Another striking observation (not shown in these figures) is that for every game, the size of the interesting parameter cases shrinks toward zero as we increase the number of players.

Our second result is that, even in the parameter ranges in which information plays a role, that role is limited. In all games, the maximum percent increase in expected payoff as a result of additional information is around 18%. This occurs in the weakest link game with exactly four players, and under fixed costs of protection and self-insurance that are set to produce maximum information impact. So having information about costs and risks of others is not a dominant factor – in other words, using educated guesses to predict these values does not hurt the bottom line too much. In contrast with this observation, the expected payoff of the naïve player is greatly reduced as a result of his imperfect situational perception. So if network users do not understand the interdependent nature of their security threats, their payoff is greatly reduced. This feature is illustrated by example for each game in Figure 3.

3.2 Value of information

The degree of darkening in the graphs of Figure 2 refer to a measure of the value of information which allows us to quantify the payoff increase due to better information for expert agents. It is nontrivial to arrive at a definitive answer for this quantity's best measure, but we consider the following ratio definition as a first step towards the goal of reasonably quantifying the value of information:

$$\frac{\text{Expected payoff in the complete information environment}}{\text{Expected payoff in the incomplete information environment}}$$



(a) Weakest link (b) Best shot (c) Total effort

Fig. 3. Expected payoffs under the various information conditions as a function of self-insurance costs. (Here we have fixed the initial endowment M and the potential loss L at unit value 1, and we have fixed the cost of protection at $b = 0.2$).

4 Conclusions

In our work we emphasize that security decision-making is shaped by the structure of the task environment as well as the knowledge and computational capabilities of

the agents. In our model, decisions are made from three distinct security actions (self-protection, self-insurance or passivity) to confront the security risks of weakest-link, best shot and total effort interdependencies [4, 14]. In these environments, we investigate the co-habitation of a single fully rational expert and $N - 1$ naïve agents. The naïve agents fail to account for the decisions of other agents, and instead follow a simple but reasonable self-centered rule-of-thumb. We further study the impact of limited information on the rational agent's choices.

We find that in general, the naïve agents match the payoff of the expert when self-insurance is cheap, but not otherwise. Even with limited information, the sophisticated agent can generally translate her better structural understanding into decisions that minimize wasted protection investments, or an earlier retreat to the self-insurance strategy when system-wide security is (likely) failing.

To analyze the impact of the different information conditions we have proposed a new mathematical formalization. We measure the value of complete information as the ratio of the payoff in the complete information environment to the payoff in the incomplete information environment. Our analysis of Figure 2 is a first step in that direction, however, a more formal analysis is deferred to a companion research paper [7].

Finally, a system designer is not only interested in the payoffs of the network participants given different information realities (e.g., due to frequent changes in attack trends). He is also concerned with how well-fortified the organization is against attacks. To that effect we plan to include a more thorough presentation of the parameter conditions that cause attacks to fail due to system-wide protection, and when they succeed (due to coordination failures, passivity, and self-insurance).

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