



Interaction, protection and epidemics[☆]

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ABSTRACT

Individuals respond to the risk of contagious infections by restricting interaction and by investing in protection. We develop a model that examines the trade-off between these two actions and the consequences for infection rates.

There exists a unique equilibrium: individuals who invest in protection choose to interact more relative to those who do not invest in protection. Changes in the contagiousness of the disease have non-monotonic effects: as a result interaction initially falls and then rises, while infection rates too may initial increase and then decline.

We then consider a society with two communities that differ in their returns from interaction – High and Low. Individuals in isolated communities exhibit different behavior: the High community has a higher rate of protection and interaction, and a lower rate of infection. Integration amplifies these differences.

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1. Introduction

Interactions between individuals generate value, but facilitate the spread of infections. This tension is salient in diseases such as influenza, HIV and tuberculosis, but also applies to the Internet and other digital networks.¹ In all these examples, infection spreads primarily through interpersonal contacts: so prevalence can be reduced by restricting interaction and/or by investing in protection. This paper develops a model that examines the trade-off between these two courses of action and its consequences for the spread of infections.

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¹ There are 3 to 5 million cases of acute influenza and between 250,000 and 500,000 deaths are attributed to this infection, annually. In 2012, over 8.5 million people were infected with tuberculosis and 1.3 million deaths were attributed to it. In the same year, 2.3 million new cases of AIDS were reported and over 1.5 million people died due to the disease; over 36 million people have died due to HIV/AIDS so far (WHO, 2013, 2014a,b). The Internet reflects a similar tension: on-line interactions generate rewards but may serve as a conduit for the spread of viruses and worms which compromise user value. As energy, communication, travel, consumer interaction increasingly adopt digital networks, cyber-security has emerged as a major concern. We discuss the relevance of our analysis for cyber-security later in the introduction.

In our model, a population faces the risk of becoming infected. Every individual chooses how much to interact with others in the population, and whether or not to protect himself. Interactions generate benefits but increase the risk of infection from infected others. Protection is available, at a fixed cost. The protection rate, the profile of interaction, and the contagiousness of the infection together determine the extent of the disease in the population.

We first establish that a (Nash) equilibrium exists and is unique. For a broad class of circumstances, equilibrium protection rates are interior: only a part of the population protects. Individuals who invest in protection interact more than those who do not. Restricted interaction and protection are substitutes. This relation is consistent with empirical observation. For example, in their well known study on British sexual attitudes and behavior, Wellings et al. (1994) report a positive correlation between the frequency of new partners and the use of condoms.

The contagiousness determines the probability of becoming infected from interacting with infected individuals, and is a key parameter in the study of epidemics.² We find that equilibrium response to contagiousness is non-monotonic. There exists a threshold level of contagiousness: below this value, protection rates are zero, and the response to higher contagiousness is through reduced interaction only. This threshold reflects the fixed costs associated with protection: below the threshold incurring the costs is not worthwhile. Above the threshold, returns from protection outweigh costs. Greater contagiousness now induces greater

² For a classical exposition of the theory of epidemiology, see Anderson and May (1991). For a recent survey on epidemics, see Gersovitz (2011).

protection, and a first-order stochastic dominance shift in the profile of interaction. Infection rates too may vary non-monotonically – initially increasing and then declining – in contagiousness.

In our basic model individuals are homogenous. We then turn to a society with two communities that differ in their returns from interaction – High and Low. Individuals in isolated communities exhibit different behavior: the High community has a higher rate of protection and interaction. As communities integrate, protection and interaction further increase in the High community while they fall in the Low community. Integration thus leads to falling (rising) infection in the High (Low) community.

The theoretical prediction on the relation between returns and equilibrium behavior is broadly consistent with empirical observation. Wellings et al. (1994) report that single people have more partners and are much more likely to use condoms as compared to cohabiting couples. Philipson and Posner (1993) report a negative correlation between education/income and HIV infection: they surmise that higher income raises the returns from the future and thereby leads to greater investments in protection (the use of condoms). This in turn lowers the rate of infection.

Our model and its predictions are also related to cybersecurity.³ The equilibrium property of positive correlation between protection and interaction is consistent with the findings of Anderson et al. (2007) and Moore et al. (2011) on the positive relation between investments in security and Internet use. The model predicts that the High community will have higher protection and interaction: this is consistent with the fact that larger firms are more active in securing themselves as compared to smaller firms (Anderson et al., 2007).

Our paper is a contribution to the economic study of epidemics and cybersecurity. It is useful to separate the existing research in economic epidemiology into two strands. The first strand of work takes interaction as given and explores the response in protection rates. This work includes Brito et al. (1991), Geoffard and Philipson (1996, 1997), Francis (1997), Goldman and Lightwood (2002), Gersovitz and Hammer (2004), Galeotti and Rogers (2013), and Chen and Toxvaerd (2014). A second (and complementary) group of papers assumes that protection is absent and studies the response in interaction. This work includes Philipson and Posner (1993) and Kremer (1996). To the best of our knowledge, the present paper is the first attempt to provide a unified treatment of interaction and protection. The analysis yields a number of new insights; we highlight two of them via a comparison with the benchmark models.

Compared to the ‘pure protection’ benchmark, our model yields lower rates of protection. This is because part of the population foregoes protection and responds instead by adapting interaction. But compared to that benchmark, infection rates are higher in our model. This tells us that differences in protection are ‘insufficiently’ compensated for by restricted interaction.

Consider next the ‘pure interaction’ benchmark, where protection is unavailable. The more a susceptible interacts, the greater the chances that he becomes infected and, in turn, transmits the disease to others around him. ‘Pure interaction’ models are thus characterized by the property that increasing returns from interaction raises infection (Kremer, 1996). In our setting, on the other hand, the more individuals value interaction the less inclined they are to respond to an epidemic by reducing interaction. This implies that higher returns from interaction lead to higher protection rates and – in sharp contrast to the ‘pure interaction’ benchmark – to lower infection.

³ Estimates of the costs of cyber crime vary greatly. A recent study estimates the costs to be in the range of 300 billion USD to 1 trillion USD; this is between 0.4% and 1.4% of global GDP. A recent study for the UK Cabinet Office reported that the cost to the UK economy is over 27 billion USD per annum (Detica and Cabinet Office, 2011). In 2009, roughly 10 million computers were infected with malware designed to steal online credentials. The annual damages caused by malware is of the order of 9.3 billion Euros in Europe, while in the US the annual costs of identity theft are estimated at 2.8 billion USD Moore et al. (2011).

Our results have potential policy implications. A first order implication is that demand for protection will be lower in a model where interaction levels are a choice variable.⁴ An important insight from the economic models of epidemiology is the externality in individual protection. In our model, choosing protection creates an additional externality: protected individuals interact more and this alters the pool of contacts. We show that this expands the scope for policy intervention, as compared to the ‘pure protection’ benchmark. Finally, our work suggests that subsidies on protection should target those valuing social interaction least, as doing so minimizes crowding-out effects.

The problem of computer network security has been extensively studied in electrical engineering and computer science; for an overview of this work see Alpcan and Basar (2011) and Anderson (2008). Aspnes et al. (2006) (and the literature that follows them) study protection choices by nodes faced with a viral infection that spreads through a given network. Our paper contributes to this literature by proposing a general framework in which interaction (network) and security investments are both endogenous.

The rest of the paper is organized as follows. The basic model is presented in Section 2, and analyzed in Section 3. Section 4 studies heterogeneity. Section 5 concludes. All proofs are presented in the online-appendix.

2. Model

The basic model has the following features. A continuum of individuals live for two periods. Each period, the agents individually decide how much social interaction to have (in a bar say, or in on-line activity). Social interaction is beneficial, but has drawbacks: interaction in the first period raises chances of a contagious infection, which reduces pay-offs in the second period. To mitigate the chances of infection, each agent faces two options. He may reduce interaction in the first period, or invest in protection. The protection rate, the profile of interaction, and the contagiousness together determine the fraction of the population who become infected. We next lay out the details and notation of this model.

2.1. Social interaction

A typical agent is labeled i . We let $k_{it} \geq 0$ denote the socialization ‘effort’ of agent i in period $t = 1, 2$: each period, i selects k_{it} individuals uniformly at random from the pool of available contacts.⁵ We borrow this interpretation from Kremer (1996).⁶ Given an arbitrary subset A of individuals, the probability that a new contact of i is with an individual in A is

$$\mathbb{P}_i(\text{select contact in } A) = \frac{\int_{j \in A} k_{jt} dj}{\int_{j \in [0,1]} k_{jt} dj}. \quad (1)$$

2.2. Infection

There are two ways to become infected. An individual may become infected exogenously, with probability $\epsilon > 0$. Or an individual may

⁴ The experience with swine flu vaccines is worth mentioning in this regard. Most OECD countries have large stocks of swine flu vaccines; for instance, in England, the NHS stock is estimated to have around 40 million vaccines in stock. This large stock of vaccines has provoked much discussion in recent years. Our theoretical result points to one relatively unexplored reason for this large stock: lowered international travel and interaction in response to public measures on quarantine and the fears of epidemic.

⁵ The assumption on uniform selection is relaxed in Section 4, when considering heterogeneous populations. There, we allow for ‘search’ to be directed.

⁶ As in Kremer (1996), we abstract from strategic complementarity in social interactions. Making strategic complementarities more explicit and significant would introduce the possibility of multiple equilibria. While this would enrich the analysis, our thought is that the key trade-offs we identify would remain important in this richer framework.

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