What Matters Most: Information or Interaction? The Importance of Behavioral Rules on Network Effects for Contagion Processes

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What matters most: Information or Interaction?  
The Importance of Behavioral Rules on Network Effects for Contagion Processes  

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Abstract  
We consider a finite population of agents and define a contagion process as the dynamics by which an action, which is initially played by only a small subset of agents, is adopted by the entire population. Each agent has a set of neighbors with whom he shares information and a set of partners with whom he plays a game. These two sets may or may not coincide. Each period, agents choose their actions based on what they observe from their neighbors, and get some payoff from playing a game with their partners. We show that contagion of an action that is risk dominant and efficient is obtained through partners when agents imitate-the-best, and through neighbors when agents use a myopic best response.
1 Introduction

A common assumption in the network literature is that a link between two people captures both information sharing and interaction activities, where interaction often means playing a game. Only a few studies, such as those by Durieu and Solal [2] and Alós-Ferrer and Weidenholzer [1] consider these two activities as distinct. The argument presented by Alós-Ferrer and Weidenholzer is that although interactions are predominantly local, information sharing is often a broader activity. Hence, agents who do not play games with each other can still gather information from one another. A consequence of this assumption is that there cannot be any interaction among strangers. However, this is not always the case in real life situations. For example, understanding how viruses spread in a population necessitates the acknowledgment that people do not always interact with whom they know. In most cases, people do get contaminated because they did not know the person they were interacting with was infected. The human sexual contact network and the transmission of diseases such as herpes or HIV illustrates this point quite clearly. Furthermore, this is not just a matter of distinguishing clearly between information and interaction. As it may take several months or years for someone to learn about their condition, it is primordial to capture the fact that interactions can happen without any information transfer, or that this information transfer happens so long after the interaction that it becomes almost irrelevant. Hence, not only are information sharing and interaction distinct activities, but the people with whom one interacts may differ from those whom one acquires information. The assumption that people only interact with those they know needs further study. Therefore, our aim is to investigate whether such assumption is innocuous in contagion processes when information and interaction networks are distinct, and potentially different. Specifically, in this paper we show that allowing separation between information and interaction networks can drastically alter previous results obtained in the contagion literature.
We are not the first to investigate contagion processes within networks. In his paper, Morris [6] considers an infinite population of agents who are part of an arbitrary network. A link represents both the exchange of information and the interaction that take place between two agents. Each period, agents play a game with a finite subset of the population and choose one of two possible actions. The game considered presents two strict Nash equilibria. The action choice is determined by a myopic best response to the frequency of plays in the population in the previous period. An action is said to be contagious if it spreads to the entire population when it is initially played by only a finite subset of agents. The main focus of Morris’ paper is to characterize, through some qualitative properties of the network, the contagion threshold of the network, i.e. the number of agents needed to promote the contagion of a given action. In particular, Morris shows that an action can only spread if it is risk dominant, as defined by Harsanyi and Selten [4]. An extension of Morris’ work by López-Pintado [5] provides the exact contagion thresholds of random networks using particular connectivity distributions. Other papers such as the ones by Durieu and Solal [2] and Alós-Ferrer and Weidenholzer [1] also study similar contagion processes within networks. Both studies consider a game which presents two strict Nash equilibria, one of which is either risk dominant, efficient or both. Durieu and Solal [2] consider a finite population of agents placed on a circle and study the contagion of the risk dominant action when agents use best response. Alós-Ferrer and Weidenholzer [1] consider arbitrary networks and look at the contagion of the efficient action when agents play imitate-the-best.

Our paper builds on Morris [6] and defines a contagion process as the dynamics by which an action, which is initially played by only a small subset of agents in a population, is adopted by the entire population. We consider a finite population of agents who exchange some information and interact with one another. The game we consider is similar to those used by Durieu

However, we depart from the previous literature in that we make an explicit distinction between interaction and information. We characterize two distinct networks using simulation methods. An information network is defined as a network in which a link represents an exchange of information between two agents, and an interaction network is defined as a network in which links represent interactions among agents. Furthermore, we consider both best response and imitate-the-best decision rules. The reason for considering both rules is that one is based on frequency of plays while the other focuses on payoffs. Also, our main interest differs from Morris [6] and López-Pintado [5] as we do not look at contagion thresholds, but rather we are interested in whether contagion uses either interaction or information or both to spread. Finally, we introduce small world networks as defined by Watts and Strogatz [8] in addition to the exponential, scale-free and homogeneous networks, presented by López-Pintado [5]. As these networks are not characterized by a particular connectivity distribution they allow us to understand whether our results are tied with connectivity distributions or not.

We replicate the results of López-Pintado [5] when information and interaction networks are the same and show that the separation of information and interaction networks results in different outcomes. We show that agents' behavior dictates which network, interaction or information, matters most for contagion. With best response, information leads contagion while with imitate-the-best, contagion spreads through interactions. Although theoretical, these results have important implications in policies. For example, consider the spread of the H1 virus. If the population’s behavior is guided by frequencies of plays, then information campaigns may indeed be worth the spending. On the other hand, if people are imitators, money will be better spent on quarantine programs.
This paper is organized as follows. Section 2 describes the networks considered, how we generate them, the game played and the behavioral rules used by the agents. In Section 3, we show how results vary between situations where information and interaction networks are the same in contrast to situations in which they are distinct. Section 4 concludes.

2 The Model

We consider a finite population of agents $N = 1, 2, ..., i, ..., n$ who engage in interaction and information sharing activities. Each agent has a set of neighbors, with whom he shares information and a potentially different set of partners, with whom he interacts. The exchanges of information between neighbors constitute an information network while the interactions among partners define an interaction network. It is possible for a neighbor to also be a partner, and vice versa, but we are interested in situations where this is not always the case.

Each period, agents play a $2 \times 2$ game with each of their partners and choose one of two possible actions. Agent $i$’s choice of action depends on the information he gathers from his neighbors and his payoff is the sum of the payoffs obtained from each of his pairwise interactions. Once agents played and obtained their payoffs, one agent is selected at random with positive probability to revise his action. His payoffs and his partners’ payoffs are then updated, and the next period starts.

These dynamics define a Markov process over the set of all possible states, where a state is a vector that specifies the action played by each agent. We are interested in understanding the influences of information and interactions on contagion processes, i.e. the dynamics by which the Markov process converges to a state where all agents play the same action.
2.1 Networks

In our framework, a network, whether it is an information or an interaction network, is an undirected graph where the vertices represent the agents and the links capture the activities between agents.

2.1.1 Interaction vs Information

In an information network, a link represents an exchange of information between two agents, where an agent’s information has two elements: the agent’s last played action and associated payoff. Hence, we represent an information network as an undirected graph with adjacency matrix $L$, where $l_{ij} = 1$ if there is a link between $i$ and $j$ and $l_{ij} = 0$ otherwise. For each agent $i$, we define a set of neighbors as $N_i = \{ j \in N \ s.t \ l_{ij} = 1 \}$. We do consider that agent $i$ is a neighbor of himself, i.e. $l_{ii} = 1$.

Similarly, in an interaction network, a link between two agents represents the fact that these two agents play the game together each period. Interactions are modeled using a graph with adjacency matrix $M$, where $m_{ij} = 1$ if there is a link between $i$ and $j$ and $m_{ij} = 0$ otherwise. Each agent $i$ has a set of partners that is defined as $P_i = \{ j \neq i \in N \ s.t \ m_{ij} = 1 \}$. Note that although we assume that agent $i$ can observe his own action and payoff, he does not interact with himself.

As stated earlier, we look at cases where information and interaction networks are distinct. This allows us to disentangle the effects of information and interactions on contagion processes. We follow the literature and focus our attention on some particular network types that we introduce in the following section.

2.1.2 Types of Networks

Let $k_i$ be the connectivity of agent $i$. The connectivity of agent $i$ is the number of links agent $i$ has with other agents. It is the number of agent $i$’s
neighbors if we consider the information network, and it is the number of agent \(i\)'s partners if we look at the interaction network. Hence,

\[
P(k) = \frac{1}{n} \text{Card} \{i \in N \text{ with } k_i = k\}
\]

represents the connectivity distribution of a given network.

In this paper, we focus our attention on four types of networks: homogeneous, exponential, scale-free and small-world. An homogeneous network, or regular graph, is one where \(k_i\) is exactly \(k\) for all \(i\). An exponential network presents a connectivity distribution that peaks at an average \(<k>\) and decays exponentially for large \(k\). A scale-free network has a connectivity distribution \(P_{SF}(k) \approx k^{-\gamma}\) with \(\gamma\) usually between 2 and 3. This allows some nodes to have very high connectivity.

Finally, small-world networks of Watts and Strogatz [8] are not characterized by their connectivity distribution but rather by their overall path-length and their clustering coefficient. The overall path length is the average number of hops between one node and every other node. The clustering coefficient is the proportion of an agent’s neighbors who are also neighbors with one another in the information network. A similar definition applies to the interactions network. The characteristics of small-world networks is that they have a small average path length and a high clustering coefficient, compared to a Erdős and Rényi (Bernouilli) random graph [3] with the same number of nodes and equivalent average degree of connectivity. The integration of small world networks in our study allows us to understand whether our results are fundamentally linked with specific forms of connectivity distributions.

The fact that small-world networks are not characterized by their connectivity distribution implies that it is possible for example to have a small-world network that has a scale-free distribution, or a scale-free network that has the characteristics of a small-world. If this happens too often, there will be no difference in our results between scale-free networks and small-worlds. In order to avoid this phenomenon, for each trial and each type of
network, we picked one network among the hundred networks we generated. It minimizes the likelihood of generating only scale-free small-worlds and eliminates the risk of getting results for a very peculiar set of networks.

Scale-free and exponential networks were built following the algorithm proposed by Newman et al. [7]. Log-likelihood tests of the resultant power-law degree distribution generated $\alpha$ as given, and $L = -11.5$ ($x_{\text{min}} = 4$). The exponential distribution was tested with a standard transformed OLS procedure with $\alpha$ as given, $t$–statistic 30.9 and $R^2 = 0.98$. Homogeneous and small-world graphs were built following the local wiring approach as in Watts and Strogatz [8]. A rewiring probability of 1 was used to produce each small-world network. Figure 1 illustrates the shapes of the networks considered in this paper, while Table 1 summarizes their characteristics. All the graphs we generate are connected, i.e. there is always a sequence of links from one agent to any another agent. This avoids the absence of contagion due to isolated nodes in either networks. Furthermore, we compare graphs with similar average degrees to avoid unwanted network effects.

Figure 1: Example networks studied in this paper: a) Scale-free; b) Exponential; c) Homogeneous; and d) Small-world.
Table 1: Properties of graphs presented in this paper.

<table>
<thead>
<tr>
<th></th>
<th>Scale-free</th>
<th>Exponential</th>
<th>Homogeneous</th>
<th>Small-world</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P(k)$</td>
<td>$k^{-\alpha}$</td>
<td>$e^{-k/\alpha}$</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>2.7</td>
<td>8.3</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\langle k \rangle$</td>
<td>7.6</td>
<td>7.9</td>
<td>8.0</td>
<td>8.0</td>
</tr>
</tbody>
</table>

2.2 Dynamics of the Game

Each period, each agent interacts with each of his partners and chooses an action from the space $S = \{0, 1\}$. Payoffs from each pairwise interaction are summarized in the following symmetric matrix:

\[
\begin{array}{ccc}
  & 0 & 1 \\
 0 & b & f \\
1 & e & d
\end{array}
\]

where $d > f$ and $b > e$ so that the game is a coordination game with two strict Nash Equilibrium $(0, 0)$ and $(1, 1)$.

Let $q = \frac{b-e}{d-f+b-e}$ be the probability associated with playing 1 in the mixed strategy Nash equilibrium. If $q \leq 1/2$, then action 1 is said to be risk dominant as defined by Harsanyi and Selten [4]. The lower the value of $q$, the more risk dominant action 1 is. Player $i$’s total payoff $\Pi_i$ at the end of the period is the sum of his pairwise interactions’ payoffs:

\[ \Pi_i = \sum_{j \in P_i} \pi(s_i, s_j) \]

where $\pi(s_i, s_j)$ can be read in the above matrix and $s_i, s_j \in S = \{0, 1\}$.

2.3 Behavioral Rules

We assume that agents use either one of two common decision rules: myopic best response and imitate-the-best. The choice of these rules is motivated
by the fundamental differences that exist between them. The myopic best response focuses on frequency of plays while imitate-the-best focuses on payoffs. Hence, best-response gives more importance to information than interactions, as what matters for an agent’s decision is the frequency of plays within his neighborhood, and hence, whoever interacts with whom is irrelevant. For imitate-the-best, interactions do matter as they determine the payoffs, but the decision regarding which action to play is still made through the observation of the payoffs. Hence, with imitate-the-best, it is not clear which is matters most: information or interactions.

Furthermore, we do not consider any mixing of the two rules within the population, i.e. for any given experiment, all agents follow the same rule. This allows us to highlight why, when a decision rule is based rather on frequency of actions than payoffs (and vice versa), it is primordial to correctly specify and separate the information network from the interaction network.

We study the contagion of action 1, the risk dominant action, as contagion of action 0 cannot occur with best response as demonstrated by Morris [6]. Hence, the starting state contains only a very small fraction of agents playing 1. When agents use the imitate-the-best rule, we had to increase the proportion of agents playing 1 at the start of the game in order to obtain contagion. This does not affect our results in any way, as we will explain later.

For myopic best response, we assume that all agents react to the distribution of plays within their neighborhood. In our case, it means that player $i$ chooses 1 if he observes that the proportion of his neighbors playing 1, excluding himself, is higher than $q$. The reason why we exclude agent $i$ from the sample is because when using best response, player $i$ samples from others to see what he will likely encounter. He then makes his response to the rest of the world appropriately. Since his own play is being changed subject to others, it is non-sensical for him to include himself.
If agent \( i \) plays using the imitate-the-best rule, he chooses the action that gave him or his neighbors the highest payoff in the previous period. In this case, we assume that player \( i \) includes his own past experience in his decision. He samples from his neighbors because he considers that what they have experienced (i.e. their payoffs) could be a good proxy for what he is likely to experience. If his neighbors experienced a higher payoff than himself, then he rightly tries out their strategy.

3 Results

Each trial, we choose one network from a set of 100 networks in the database (for a given network type) we generated. We then identify the probability of full contagion for each type of network structures and each combination of network structures. The results presented below were obtained with a game where \( d = 5, b = 1, e = f = 0 \), and hence, \( q = \frac{1}{6} \) and the outcome of the strategy profile \((1,1)\) is risk dominant and efficient. Results are similar for different games, as long as \( q < \frac{1}{2} \) and the equilibrium is risk dominant and efficient.\(^1\)

When the game considered presents a risk dominant equilibrium which is not efficient, the results are identical for best response, but differ with imitate-the-best. This is due to the fact that imitation favors the efficient strategy (strategy 0), and hence, contagion of action 1 is unlikely to occur when the risk dominant action is not efficient.

We initialize the percentage of agents playing action 1 at the start of the simulations at 1% when best response is used. With imitate-the-best, we move to initialization with 5%. The reason for the change in initial conditions is explained by the fact that with imitation, the contagion process is harder to start. Since we are comparing networks to one another, keeping the decision rule and starting conditions constant, this does not compromise

\(^1\)Simulations results for games with different parameter values are available from the authors upon request.
our results in any way.

### 3.1 Identical Networks

Fig. 3.1 reports the probability of full contagion, when interaction and information networks are identical, showing data convergence under best response with number of trials for the four different networks: Scale-free (○), Exponential (△), Homogeneous (×) and Small-world (+). After 500 trials, the signal from the simulation had settled down sufficiently to begin comparing experiments. To be sure, all simulations to follow were run for 1000 trials with subsequent statistical test conducted on this larger number of repeats.

![Figure 2: Probability of full contagion for each type of networks, 1000 trials.](image)

When information and interaction networks are identical, the percentage of networks for which full contagion is obtained depends on the network type,
as shown in Table 2. Recall that the relative values between best response and imitate-the-best do not matter as initial conditions differ.

Table 2: Percentage of full contagion when identical networks

<table>
<thead>
<tr>
<th></th>
<th>Scale-free</th>
<th>Exponential</th>
<th>Homogeneous</th>
<th>Small-world</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best response</td>
<td>18.9</td>
<td>14.8</td>
<td>2.7</td>
<td>4.3</td>
</tr>
<tr>
<td>Imitate-the-Best</td>
<td>33.6</td>
<td>23.2</td>
<td>13.2</td>
<td>13.2</td>
</tr>
</tbody>
</table>

The comparison of proportions by \textit{p-values} for fraction of trials ending in full contagion when information and interaction networks are identical are presented in Table 3. The test we used was built as follows. Given the hypothesis for two proportions $p_1 = p_2$ with equal sample size $n$, the relevant test-statistic reduces to:

$$z = \frac{(\hat{p}_1 - \hat{p}_2)}{\sqrt{2\hat{p}(1-\hat{p})/n}},$$

where $\hat{p} = (x_1 + x_2)/(2n)$ for count $x_1$ and $x_2$ of successes in each sample of size $n$ respectively. Underline indicates $p \leq 2.5\%$ (i.e. significance at 5\% level (two-tailed)), boldface indicates $p \leq 0.5\%$ (i.e. sig. at 1\% level (two-tailed)). This convention is used for all subsequent Tables unless otherwise stated. Therefore, a bold underline number means that the percentage of trials ending in full contagion for the two considered networks is statistically different at a level of 1\%. If the number is only underline, the difference is statistically accepted at 5\%. 

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Table 3: Comparison of proportions by *p*-values for fraction of trials ending in full contagion

<table>
<thead>
<tr>
<th></th>
<th>Exponential</th>
<th>Homogeneous</th>
<th>Small-World</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale-Free</td>
<td>0.016</td>
<td><strong>0.000</strong></td>
<td><strong>0.000</strong></td>
</tr>
<tr>
<td>Best</td>
<td></td>
<td><strong>0.000</strong></td>
<td><strong>0.000</strong></td>
</tr>
<tr>
<td>Response</td>
<td>Homogeneous</td>
<td></td>
<td>0.974</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Exponential</th>
<th>Homogeneous</th>
<th>Small-World</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale-Free</td>
<td><strong>0.000</strong></td>
<td><strong>0.000</strong></td>
<td><strong>0.000</strong></td>
</tr>
<tr>
<td>Imitate-the</td>
<td><strong>0.000</strong></td>
<td><strong>0.000</strong></td>
<td><strong>0.000</strong></td>
</tr>
<tr>
<td>-best</td>
<td>Homogeneous</td>
<td></td>
<td>0.5</td>
</tr>
</tbody>
</table>

*Notes:*
- Underline indicates $p \leq 2.5\%$ (i.e. significance at 5% level (two-tailed)), boldface indicates $p \leq 0.5\%$ (i.e. sig. at 1% level (two-tailed)).

These results show that, with either decision rule, different networks lead to different success rates of contagion, with the exception of small-world and homogeneous graphs. Hence, when both networks are identical, successful contagion mainly depends on the network structures considered. The similarity of small-world and homogeneous can be explained by the fact that homogeneous networks are used to generate small-worlds. Therefore, small-worlds may still present very similar characteristics to homogeneous networks thus explaining why the *p*-value is not significant. These results constitute the benchmark of our study.

### 3.2 Distinct Networks

For each type of networks, the proportions of networks for which full contagion arises, with either best response or imitate-the-best, are reported in Table 4. The lines represent the interaction networks whereas the columns
represent the information networks. Hence, the first line shows the percentage of full contagion for a scale-free interaction network, under best response, when the information network is scale-free, exponential, homogeneous or small-world. The first column shows the percentage of full contagion for a scale-free information network, when the interaction network is scale-free, exponential, homogeneous or small-world, under best response first, and then under imitate-the-best.

Table 4: Percentage of full contagion when distinct networks

<table>
<thead>
<tr>
<th>INF</th>
<th>Scale-free</th>
<th>Exp.</th>
<th>Homog.</th>
<th>Small-world</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale-free</td>
<td>19.4</td>
<td>13.5</td>
<td>4.2</td>
<td>5.0</td>
</tr>
<tr>
<td>Best I Exponential</td>
<td>18.7</td>
<td>4.8</td>
<td>3.3</td>
<td>5.2</td>
</tr>
<tr>
<td>Response N Homogeneous</td>
<td>19.8</td>
<td>5.2</td>
<td>3.5</td>
<td>3.7</td>
</tr>
<tr>
<td>T Small-world</td>
<td>19.0</td>
<td>4.1</td>
<td>4.4</td>
<td>3.8</td>
</tr>
<tr>
<td>Scale-free</td>
<td>15.3</td>
<td>18.5</td>
<td>18.3</td>
<td>15.3</td>
</tr>
<tr>
<td>Imitate-the I Exponential</td>
<td>17.0</td>
<td>14.5</td>
<td>13.7</td>
<td>13.0</td>
</tr>
<tr>
<td>-best N Homogeneous</td>
<td>7.6</td>
<td>7.0</td>
<td>12.2</td>
<td>13.3</td>
</tr>
<tr>
<td>T Small-world</td>
<td>8.6</td>
<td>9.6</td>
<td>13.8</td>
<td>10.9</td>
</tr>
</tbody>
</table>

In order to isolate the effects of information, we consider simulations for which the interaction network is invariant. The results presented below in Table 5 are for a scale-free interaction network, but similar results are obtained with other types of interaction network.
Table 5: Comparison of proportions by \textit{p-values} for fraction of trials ending in full contagion with invariant scale-free interaction network

<table>
<thead>
<tr>
<th>Inv. Interaction</th>
<th>Information Network</th>
<th>Exponential</th>
<th>Homogeneous</th>
<th>Small-World</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net: SF</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information</td>
<td>Scale-Free</td>
<td>0.015</td>
<td>\textbf{0.000}</td>
<td>\textbf{0.000}</td>
</tr>
<tr>
<td>Network</td>
<td>Exponential</td>
<td></td>
<td>0.000</td>
<td>\textbf{0.000}</td>
</tr>
<tr>
<td>(Best response)</td>
<td>Homogeneous</td>
<td></td>
<td></td>
<td>0.803</td>
</tr>
</tbody>
</table>

| Information      | Scale-Free           | 0.2243      | 0.964       | 0.500       |
| Network          | Exponential          |             | \textbf{0.995} | 0.776       |
| (Imitate-the-best) | Homogeneous     |             |             | 0.036       |

Notes:

Underline indicates $p \leq 0.025$ (i.e. significance at 5% level (two-tailed)), boldface indicates $p \leq 0.005$ (i.e. sig. at 1% level (two-tailed))

With an invariant interaction network, the results depend on the decision rule considered. For best-response, the results we obtained are similar to our benchmark. This means that the isolation of the interaction network did not matter, and that the proportions of full contagion vary with the type of the information network. This suggests that with best-response, contagion occurs through the information network.

With imitate-the-best, these results differ considerably from our benchmark. When the interaction network is invariant, the proportion of trials ending in full contagion is similar for most information networks. Hence, the information network does not play a role in the contagion process. This means that when agents imitate-the-best, full contagion of action 1 is obtained through interactions.

In order to confirm our first results, we now consider a set of simulations
where the information network is invariant. Results are presented in Table 6.

Table 6: Comparison of proportions by *p*-values for fraction of trials ending in full contagion with invariant scale-free information network

<table>
<thead>
<tr>
<th>Inv. Information</th>
<th>Interaction Network</th>
<th>Exponential</th>
<th>Homogeneous</th>
<th>Small-World</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net: SF</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Interaction</em></td>
<td>Scale-Free</td>
<td>0.589</td>
<td>0.589</td>
<td>0.410</td>
</tr>
<tr>
<td><em>Network</em></td>
<td>Exponential</td>
<td></td>
<td>0.500</td>
<td>0.326</td>
</tr>
<tr>
<td>(Best response)</td>
<td>Homogeneous</td>
<td></td>
<td></td>
<td>0.326</td>
</tr>
<tr>
<td><em>Interaction</em></td>
<td>Scale-Free</td>
<td>0.887</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td><em>Network</em></td>
<td>Exponential</td>
<td></td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>(Imitate-the-best)</td>
<td>Homogeneous</td>
<td></td>
<td></td>
<td>0.794</td>
</tr>
</tbody>
</table>

*Notes:*
Underline indicates $p \leq 2.5\%$ (i.e. significance at 5% level (two-tailed)), boldface indicates $p \leq 0.5\%$ (i.e. sig. at 1% level (two-tailed)).

In the case where the information network is invariant, we observe that results are similar to our benchmark with imitate-the-best, but strongly differ with best response. With imitate-the-best, isolating the information network has no impact on the proportions of processes ending in full contagion. This confirms the observations made above, that is contagion arises through interactions when agents imitate-the-best. On the other hand, with best response, the results show that there is no difference between the interaction networks. Hence with best response, contagion spreads through the information network.
4 Conclusions

These results provide valuable insights as to which networks matters most for a given behavioral rule. They also highlight the intricate dependence between behavioral rules and networks. If agents focus on the frequency of plays, contagion happens through the information network, while if they make their decision based on payoffs levels, contagion spreads through interactions.

These results are important as they underline why, by loosely defining links between agents, results may be inaccurate. Coming back to our initial example regarding the spread of viruses or sexually transmitted diseases, our results show that it is crucial to understand whether the population behave according to frequencies of plays or outcomes levels. This does present some significant implications for policies. If people rely on frequencies of plays, informing them is worth the investment as it will shape their decision on whether to protect themselves. On the other hand, if people are imitators, information has minimal impact on the contagion process, and intervention on interactions is needed to avoid the contagion of risky behaviors. Other instances for which our results could have implications are the human sexual contact network, the Internet and eBay auctions.

References


