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Full Length Article

How chilling are network externalities? The role of network structure

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ABSTRACT

In an influential paper, Goldenberg, Libai, and Muller (2010) use an agent-based model to demonstrate that network externalities have a "chilling" effect on new product diffusion, i.e. they slow down new product adoption since many consumers wait before enough people have adopted. They perform their simulations using theoretical Moore lattices as the underlying social network of consumers. However, it has been demonstrated in other contexts that network structures can significantly affect the dynamics of new product diffusion, and hence it is worth investigating the same considerations for network externalities as well. I use the diffusion model of Goldenberg et al. (2010) to perform simulations on actual social networks to demonstrate that the chilling effect of network externalities is somewhat offset by increasing network size and average degree of the nodes, but accentuated by increased clustering in the network. My simulations also reveal that the diffusion model used by Goldenberg et al. (2010) does not have the chilling effect tautologically "baked" into it; rather network externalities do tend to slow down new product adoption most of the time, but not always.

1. Introduction

In an influential paper, Goldenberg et al. (2010) (henceforth GLM10) challenge the conventional wisdom that network externalities speed up the diffusion of new goods. Using an agent-based model, they demonstrate that network externalities in fact introduce a *chill* in the diffusion process, i.e. they initially slow down adoption, since many consumers wait before enough people have adopted. GLM10 use simple Moore neighborhoods for their simulations; a good starting point for simulating complex diffusion processes. However, it has been demonstrated in many cases that the underlying network structure significantly influences the dynamics of diffusion processes (Libai, Muller, & Peres, 2013; Rahmandad & Sterman, 2008). Thus, in the spirit of Rand & Rust (2011), given the recent availability of real world network data, it is worth investigating how their properties could influence the so-called chilling effect of network externalities, an issue not addressed by GLM10. In this paper, I use GLM10's model and perform their simulations on Moore neighborhoods and seven real world network data sets. The simulations show that the chilling effect of network externalities is somewhat offset by increasing network size and average degree of the nodes, but accentuated by increased clustering. They also reveal that under certain conditions, though rare, network externalities can actually speed up the diffusion process, and it is possible that the net present value of a new product with network externalities is higher than if there were no network externalities. This finding addresses the critique of GLM10 that their threshold-based model has a chilling effect "baked" into it and bolsters its validity.

2. Diffusion model

Here, I briefly describe the diffusion model used by GLM10. Consider a market (network) of N individuals (nodes) connected through interpersonal ties. Once a new product is released here, each individual i may adopt the product either through marketing efforts or peer influence. In the absence of network externalities, an individual adopts the good at time t with a probability

$$p_i(t) = 1-(1-a)(1-b)^{m_i(t)} \tag{1}$$

where a is the probability of adopting due to external influences like advertising, b is the probability of adopting due to peer effects, and $m_i(t)$ is the number of i's acquaintances who have adopted the good by time t. In the presence of network externalities, every individual is assumed to have a personal threshold — a minimum number of adopters across the network that would be required for her to consider adopting the product. Here, the above equation is modified as

$$p_i(t) = \begin{cases} 1-(1-a)(1-b)^{m_i(t)} & \text{if} \quad \chi(t)/N > h_i \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where $\chi(t)$ is the total number of adopters at time t in the *entire* network and h_i is individual i's personal threshold. h_i is assumed to be normally distributed with mean h and standard deviation σ, and an individual

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with $h_i < 0$ is assumed to have a personal threshold of zero. Each diffusion process is characterized by its net present value (*NPV*) with a discount rate δ.

$$NPV = \sum_t \frac{\text{sales}_t}{(1+\delta)^t} \quad (3)$$

3. Network data and simulations

Using GLM10's model, I perform their simulations on the following network structures[1]: the theoretical two-dimensional Moore neighborhood with 625 nodes (a replication of GLM10), Rovira i Virgili University's (URV) email network (Guimera, Danon, Diaz-Guilera, Giralt, & Arenas, 2003), a Facebook ego network (McAuley & Leskovec, 2012), a jazz musicians' network (Gleiser & Danon, 2003), an ego network from an online social network (OClinks) (Opsahl & Panzarasa, 2009), a UK university faculty network (Nepusz, Petróczi, Négyessy, & Bazsó, 2008), an ego network from Youtube (Libai et al., 2013) and the Pretty Good Privacy (PGP) online file sharing network's giant component (Boguña, Pastor-Satorras, Díaz-Guilera, & Arenas, 2004). Fig. 1 illustrates these networks, which differ in their size and other aggregate properties. Apart from network size, I consider two important aggregate properties, the average degree of the nodes and the transitivity (clustering) coefficient.

The degree of a node in an undirected network is defined as the number of edges originating in that node. The average degree then is the mean of the degrees of all the nodes in the network.

Clustering in a network is the tendency of the nodes to group together. Transitivity is defined as the probability of node *A* being connected to node *C* in a given network if *A* is connected to *B* and *B* is connected to *C* (Newman, 2003) and given by the relation

$$C = 3\frac{\text{number of triangles in network}}{\text{number of connected triples of vertices}}. \quad (4)$$

Table 1 lists the different properties of these networks.

I perform a series of full factorial-design simulation experiments[2] by varying each of *a*, *b*, *h* and σ/h over five levels for each network. Though *b* may be network-specific, I use the same parameter ranges as GLM10 for ease of replication.[3] This yields 625 simulation runs for each structure and 5000 runs overall. The 625 simulation runs corresponding to the Moore neighborhood represent a simple replication of GLM10, while the entire data generated by the 5000 simulations allow us to investigate how network structure influences diffusion processes with and without network externalities. Table 2 presents the diffusion model parameters used in the simulations.

Like GLM10, I consider the ratio of *NPV* with network externalities (using the threshold diffusion model) to *NPV* without network externalities to be the focal dependent variable in characterizing the chilling effect of network externalities. Fig. 2 presents histograms of *NPV* ratios obtained in the simulations. Unlike GLM10 who obtain only ratios less than one in their simulations, one may observe some rare cases where the *NPV* ratio exceeds one, a consideration that I will revisit in the following section. One may also observe that in some networks, the distribution of *NPV* ratios is more to the right than in Moore neighborhoods, with many more instances occurring close to one.

Table 3 presents the standardized coefficients of OLS regressions with the *NPV* ratio as the dependent variable and the diffusion model parameters and network properties as independent variables. The first column represents a simple replication of GLM10 on Moore neighborhoods, and the results are in close agreement. The second column presents results from 5000 simulations. All diffusion model parameters

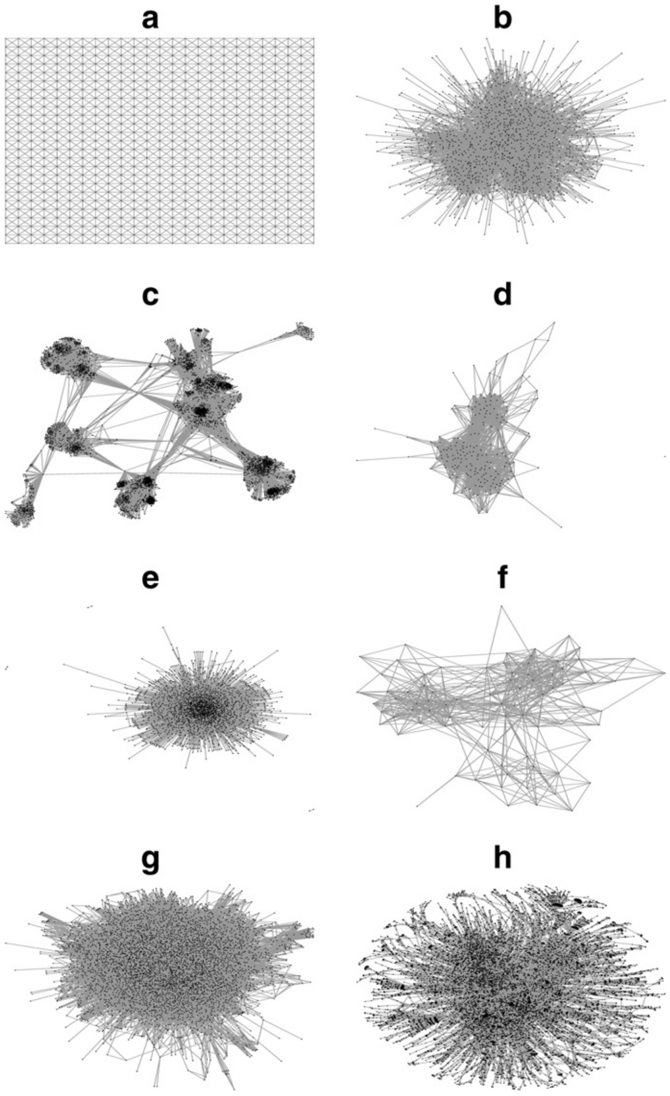

Fig. 1. Illustrations of different networks used in the simulations. (a) Two-dimensional Moore neighborhood with 625 nodes. (b) Email network at Rovira i Virgili University (URV) in Spain. (c) Facebook ego network. (d) Jazz musicians' network. (e) OClinks — online social network. (f) UK university faculty network. (g) Youtube ego network. (h) Giant component of the Pretty-Good-Privacy (PGP) online file sharing network.

Table 1
Properties of networks used in simulations.

Network	Source	Size	Average degree	Transitivity
Moore neighborhood	GLM10 — theoretical network	625	7.53	.44
URV email network	Guimera et al. (2003)	1133	9.62	.17
Facebook ego network	McAuley and Leskovec (2012)	4039	43.69	.52
Jazz musicians' network	Gleiser and Danon (2003)	199	27.56	.52
OClinks — online social network	Opsahl and Panzarasa (2009)	1899	14.57	.06
UK faculty network	Nepusz et al. (2008)	81	14.25	.47
Youtube ego network	Libai et al. (2013)	4160	8.47	.02
PGP giant component	Boguña et al. (2004)	10,680	4.55	.38
Mean		2852	16.28	.32
Standard deviation		3316	12.28	.20

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[1] I wish to thank Barak Libai for providing the Youtube data and all other authors mentioned here for making available their data on public repositories.

[2] All simulations and analyses were coded in R, using the igraph package (Csárdi & Nepusz, 2006) for analyzing network properties.

[3] I thank an anonymous reviewer for pointing this out.