CEC Dauphine | PSL

N°2020 - 09 • OCTOBER 2020

WORKING PAPER

NETWORK STRUCTURES, ENVIRONMENTAL TECHNOLOGY AND CONTAGION

Côme BILLARD [1,2*]

We represent a social system as a network of agents and model the process of technology diffusion as a contagion propagating in such a network. By setting the necessary conditions for an agent to switch (ie. to adopt the technology), we address the question of how to maximize the contagion of a technology subject to learning effects (eg. solar PV) in a network of agents. We focus the analysis on the influence of the network structure and technological learning on diffusion. Our numerical results show that clusters of agents are critical in the process of technology contagion although they generate high levels of variance in aggregate diffusion. Whatever the network structure, learning effects ease the technology contagion in social networks.

JEL CODES : O33, Q55, D91.

The author thanks Anna Creti , Arthur Thomas, Simon Quemin, Marion Dumas and Alexander Teytelboym as well as seminar and conference participants at Oxford, Paris-Dauphine University, Cambridge, Paris School of Economics, Paris I Pantheon Sorbonne, EAERE 2019 Meeting in Manchester and Ph.D. Candidates at the Climate Economics Chair.

Corresponding author : come.billard@dauphine.eu

[1*] Paris-Dauphine University, Place du Maréchal de Lattre de Tassigny, 75016 Paris
[2*] Climate Economics Chair, Palais Brongniart, 28 Place de la Bourse, 75002 Paris

KEYWORDS

Networks | Complex contagion | Technology | Learning effects | Cascades

1 Introduction

Research on diffusion in social and economic networks has focused on a wide range of topics such as diseases (Klovdhal, 1985), rumors (Moreno, 2004), systemic risks of bank failures (Elliott et al., 2014; Eboli, 2019), platform adoption (David, 1985) and patenting (Aghion, 2015). These phenomena are, at least temporarily, irreversible and share common features. First, diffusion is a social process and an individual's adoption behavior is highly correlated with the behavior of her contacts (i.e. network externalities). Second, the structure of the network plays a critical role in the propagation dynamics. While some processes remain contained in isolated clusters, others spread to the whole network. Overall, these phenomena are path-dependent : their irreversibility means that early history matters for the final outcome (Lim et al., 2016).

With respect to dynamics of propagation in networks, two main diffusion processes are frequently identified : "simple contagion" and "complex contagion" dynamics (Centola and Macy, 2007). If the former requires only one contact for transmission (e.g. information, disease), the latter calls for multiple sources of reinforcement to induce adoption (e.g. behavior, technology). On this issue, Centola and Macy (2007) demonstrated that the impact of the underlying network structure changes according to the diffusion process operating. While direct connections between agents (i.e. a short path) allow for simple contagion phenomena to spread faster, clustering (i.e. the tendency for nodes to form small groups) is a determinant of diffusion under complex contagion scenarios (Beaman et al., 2018; Centola, 2018). Then, whether the goal is to reduce contagion risk or to maximize adoption of a technology, understanding how network structures affect diffusion cascades (i.e. propagation)[1] is relevant for effective policy design.

A critical issue to explore for network studies is the case of technology diffusion (Halleck Vega et al., 2018). Particularly, technologies subject to effects of learning (i.e. costs tend to drop exponentially, at different rates that depend on the technology)[2] are of great interest as they are operating in different sectors (Farmer and Lafond, 2016). For instance, this is the case for renewables (e.g. solar PV, wind turbines, see IRENA, 2016) that must be deployed at a large scale to limit global warming "well-below" 2°C by the end of the 21st century (OECD, 2016). If the existing literature on technology diffusion is large, little attention has been paid to network perspectives (Halleck-Vega and Mandel, 2018). In particular, questions related to the spreading of a costly technology in social networks (i.e. network of individuals) and the associated impacts of network structures on diffusion remain unstudied. For the case of clean technologies, these aspects are critical as public policies support the deployment by implementing economic instruments (e.g. solar PV, biogas technology, see Blazquez, 2018). Understanding how these costly innovations spread in networks could bring new insights for designing efficient and cost saving policies. From another perspective, addressing these issues provide new perspectives on how to achieve a faster deployment of low carbon goods. In the context of climate change, increasing this body of knowledge is of great importance too.

In order to evaluate technological propagation in social networks, we build upon the Linear Threshold Model (LTM) exposed by Granovetter (1978). Our main theoretical innovation is the introduction of a technology cost function subject to learning effects. The latter gives to our approach a large scope of applications (e.g. renewables). In our agent-based model, we call "a switch" an irreversible transition to new state, such as adoption of the technology (Jackson, 2008). All agents in the network

[1] In this paper, we call "cascade" the dynamics of diffusion.

[2] See Farmer and Lafond (2016).

are initially switched off. Then, some agents are randomly switched, i.e., seeded. Every heterogeneous agent in the network is endowed with two individual thresholds. We assume that agents' thresholds are randomly and independently drawn from a uniform distribution at the start of the cascade (Kempe et al., 2003). In the following periods, if the cost of the technology falls below his first threshold and if the proportion of neighbors that switches exceeds his second threshold, the agent also switches (Granovetter, 1978; Schelling, 1978). This process propagates through the network. In our approach, one can consider neighbors as agents with shared proximity (e.g. geographic, relationship, regular contacts). Moreover, once an agent has switched, he remains switched forever. This assumption matches clean technologies investments (e.g. solar PV, biogas installation in agriculture) for which buyers cannot easily step away.

Our model assumes that agents react to stimuli both from the local and global environments (i.e. neighborhood and cost dynamics). If the social threshold is widely documented in the literature on complex contagion and threshold models (Granovetter, 1978; Watts, 2002; Dodds and Watts, 2004), we assume agents' ability to afford the technology to differ. To capture this feature, we introduce a cost threshold as a proxy measure. By doing so, we can investigate the diffusion of a costly product in social networks of heterogeneous agents. Our setting, a generalization of the Watts model (2002), is relevant as recent studies shed lights on the contagious feature of renewable technology adoption (see Baranzini et al., 2017). We consider technology spreading as an epidemic dynamics processing among agents in a network (Collantes, 2007). Then, our framework is intertwined with the "complex contagion" modelling approach as the distribution of neighborhood thresholds will require, in most cases, multiple neighbors having switched to make the considered agent switch.

With respect to underlying social structures, we apply our contagion model to three different classes of networks : lattice, small-world and random networks - as constructed by Watts and Strogatz (1998).[3] By doing so, we can investigate at a macroscopic level how diffusion spreads according to network clustering, path length and technological learning. If the notion of path length is obvious (average distance between any pair of two random agents), clustering refers to the share of peers of each node being peers among themselves (Acemoglu et al., 2011). In the literature on diffusion in networks, clustering has been extensively considered to capture the impact of network structures on diffusion (Centola and Macy, 2007; Centola, 2010; Acemoglu, 2011; Beaman et al., 2018). For our purpose, this approach is relevant as social networks tend to exhibit high levels of clustering (Watts and Strogatz, 1998; Levine, 2006). Therefrom, our comparative approach allows us to evaluate aggregate levels of diffusion, associated cascades' lengths and adoption speed of convergence from low to highly clustered networks.

Our main results suggest that aggregate diffusion reaches higher levels in lattice and small-world networks compared to random networks. The latter confirms the critical role of clustering in favouring propagation in networks. Interestingly, we also find that adoption cascades in clustered networks are subject to greater variability (variance) with respect to final outcomes (i.e. adopters). The latter has strong implications for public policy implementation. Indeed, for governments interested in maximising diffusion of, for instance, green technologies, there exists a real tension between maximising spreading and uncertainty in results. We argue that implementing economic instruments aiming at increasing affordability of the technology would limit such uncertainty. In random networks, although propagation reaches lower levels, it processes at an equivalent speed - compared to clustered networks - with a lower variability in final outcomes. In practice, the use of data from social platforms would allow governments to design policies while being aware of underlying social structures. As these platforms grow, there is a new potential to construct tools to design more effective

[3] Remember that lattice networks exhibit high levels of clustering and (comparatively) very long path length; small-world structures demonstrate high level of clustering but with lower average path length; random networks are subject to low clustering and low average path length.

policies to increase the exposure of agents to clean products. For instance, governments could match data from social platforms and technology buyers to target groups in which the product has not percolated yet. With respect to the technology, whatever the underlying structure, higher learning rates lead to larger adoption. Such findings emphasize the critical role of governments in supporting the "good" product. Further policy implications of our results are developed in the conclusion part (Section 4) of this chapter.

The theoretical literature on cascades and diffusion in networks is vast. Irreversibility of our cascade dynamics (i.e. diffusion) sets the present paper apart as a considerable part of researches supposes that agents can switch multiple times (Ellison, 1993; Blume, 1995; Young, 2006; Montanari and Saberi, 2010; Adam et al., 2012). Moreover, the double diffusion-reinforcing feedback that we introduce has, to our knowledge, never been implemented so far. Indeed, diffusion itself makes it easier for others to adopt because of the social threshold, and learning makes it easier to adopt because of the cost threshold. In contrast to some of the previous work (Acemoglu et al., 2011; Yildiz et al., 2011; Singh et al., 2013), we do not look at a particular instance of a distribution of thresholds. Instead, we assume that agents' thresholds are randomly and independently drawn from uniform probability distributions at the start of the cascade (Kempe et al., 2003). This is a reasonable assumption if the social planner has no reason to believe that some thresholds are more likely than others (Lim et al., 2016). Moreover, papers mentioned earlier (e.g. Blume, 1993; Ellison, 1993; Blume, 1995; Young, 2006; Montanari and Saberi, 2010; Adam et al., 2012) usually assume that agents play a coordination game with their neighbors and analyze the dynamics using tools from game theory. For certain problems, such as the possibility of contagion, the models are equivalent (Morris, 2000; Watts, 2002; Lelarge, 2012; Adam et al., 2012).

On the issue of technology diffusion, a recent survey on the diffusion of green technology pointed out the fundamental role of networks (Allan et al., 2014). In some of the previous works mentioned, models of innovation and technology diffusion (e.g. Centola et al., 2007; Montanari and Saberi, 2010; Acemoglu et al., 2011) provide insights on the influence of the network topology on propagation dynamics. These models consider a wide range of diffusion processes ranging from epidemic-like contagion to strategic adoption and linear threshold models. Under complex contagion, research suggests that innovations spread further across networks with a higher degree of clustering. Clusters can promote diffusion where a seed node exists inside them, but are more difficult to permeate when not targeted during the initial seeding phase (Halleck-Vega and Mandel, 2018).

By implementing the linear threshold model and introducing a technology cost function, we complement the literature and contribute to a better understanding of technology diffusion dynamics. We are dealing with large complex networks of agents interacting and switching over time (Centola et al., 2007; Centola, 2010; Acemoglu et al., 2011). As carried out in the literature, we implement our agent-based model and provide numerical analysis to capture cascades' features and build our comparative evaluation.

We proceed as follows. Section 2 describes the Watts-Strogatz algorithm (1998) to create selected networks and expose the linear threshold model. Section 3 shows and analyses numerical outcomes in terms of average aggregate adoption, speed of diffusion and time of convergence for the three classes of networks. The relevant government seeding strategy with respect to the amount of initial seeds is presented too. Finally, Section 4 discusses the main findings as well as relevant policy implications and lays out some directions for future research.

2 Model of Cascades in Networks

In this section, we present the Watts-Strogatz algorithm to generate lattice, small-world and random network. We then expose our two-threshold model of contagion in networks.

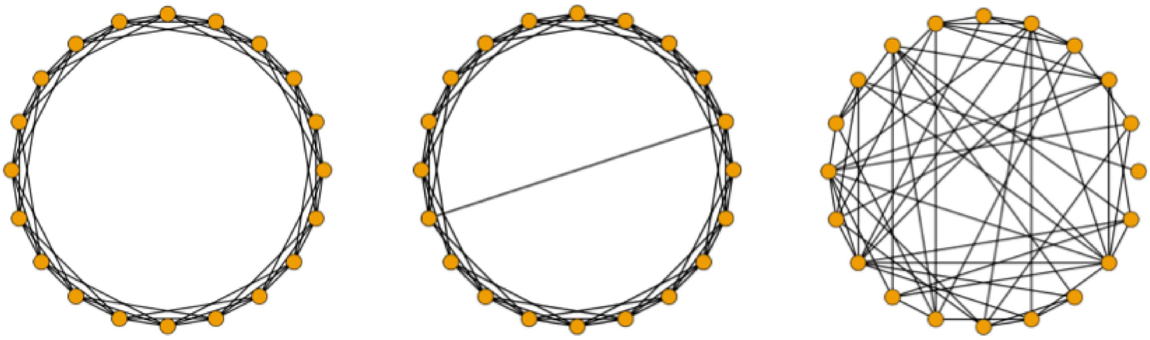
2.1 The Network

The algorithm of Watts and Strogatz (1998) is a powerful tool to create constant network density graphs ranging from nearest-neighbor networks (lattice) to uniform degree random networks. As exposed in Cowan and Jonard (2004), we assume that $I = \left\{1,\ldots,N\right\}$ represent a set of agents and for any $i, j \in I$, we define the binary variable $\chi(i, j)$ such that $\chi(i, j)$=1 if a connection exists between i and j, and $\chi(i, j)$=0, if there is no connection. Therefrom, the resulting network $G = \left\{\chi(i, j); i, j \in I\right\}$ represents all pairwise connections between agents. The neighborhood of an agent i is the total amount of her connections $\Gamma i = \left\{j \in I : \chi(i, j)=1\right\}$ while a path in G connecting i and j is a set of pairwise relationships $\left\{(i, i_1),\ldots,(i_k, j)\right\}$ such that $\chi(i, i_1) =\ldots= \chi(i_k, j)$=1. Finally, the distance $d(i, j)$ between i and j is captured by the shortest path between them.

To generate the lattice with n nearest neighbors, we consider each edge of the graph and allocate a probability p to disconnect one of its edges, and connect it to a node selected uniformly at random (with no self-connection (loop) and only one connection between two agents). By setting p, we vary the graph structure from completely regular (lattice networks with p=0), through intermediate states ($0<p<1$), to totally disordered (random networks with p=1). By doing so, we change the number of edges per agent, keeping constant an average of n connections per agent and a total of $Nn/2$ edges, $\forall p$. We denote the final network produced to be $G(n;p)$. Figure 1.1 below shows three configurations with increasing disorder as p is increased, for N=20 and n=6.

For the sake of neutrality in visualisation, networks are represented as circular layouts. This is a common procedure in social network analysis. By placing all nodes at equal distances from each other and from the center of the drawing, none is given a privileged position (Huang et al., 2007).

Figure 1: Transition from a locally ordered network (lattice) to a disordered one (random) via a small-world state. From left to right : p=0 (Lattice), p=0.1 (Small-World), p=1 (Random).



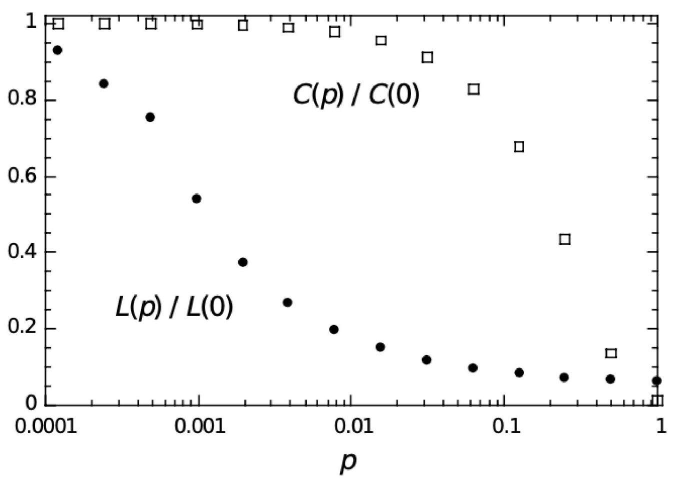
Based on the algorithm output, Watts and Strogatz suggest that the properties of such networks are captured by two complementary parameters : average clustering and average path length. Precisely, the clustering of a set $S \subseteq I$ is the proportion of pairwise relationships in S over the total possible number of relationships, that is :

$$cl(S) = \frac{\sum_{i,j \in S} \chi(i,j)}{\#S(\#S-1)/2}$$

In network science, clustering is commonly define as the share of friends of on individual who are also friends of each other. This parameter is used to measure local coherence or redundancy by taking S to be the neighborhood of an agent. Then, the local structure in the network is measured by the average neighborhood clustering $C(p) = \sum_{i \in I} cl(\Gamma_i)/N$. With respect to average path length, this measure captures the average number of edges separating two random agents (i.e. $L(p) = \sum_{i,j \in I} d(i,j)/(N(N-1)/2)$).

Although clustering and path length are strongly dependent, Watts and Strogatz expose the existence of an interval for p over which $L(p) \simeq L(1)$ yet $C(p) \gg C(1)$. The small-world network arises in such interval. The latter is due to the following : with a small amount of long distance links, their marginal effect on average path length is large because introducing a long-range link provides a shortcut between the two nodes that this edge connects, and for immediate neighbors as well, and so on. On the opposite, removing one link affects the clustering of only a small number of neighborhoods and has little effect on the population average. The evolution of path length and clustering with p is shown in Figure 1.2, where the averaged normalized values of $L(p)=L(0)$ and $C(p)=C(0)$ are plotted over a sample of 500 different graphs.

Figure 2: Average clustering and average path length as a function of p



We note that normalized average clustering remains almost constant when p is reasonably small and falls slowly for large values of p. By contrast, average path length decreases quickly for very small p values. Hence, for $p \in [0.01,0.1]$, clustering and path length diverge, creating a small-world region in the space of network structures. Therefrom, working on these three network structures allows us to investigate the role of clustering and path length on technology diffusion. Hereafter, we expose our two-threshold model of technology contagion in networks.

2.2 Technology Adoption

2.2.1 Preliminaries

We assume that technology propagates in these three classes of networks. Suppose that *G(V,E)* is an unweighted and undirected connected graph representing a set of n agents V:={1,...,n} and m links E. Neighbors of $i \in V$ are denoted as N_i*(G)*:={j|(j, i) ∈ E} and the degree of each agent i is defined as $d_i := |N_i(\mathrm{G})|$. Two thresholds are allocated to each agent $i \in V$:

- A cost threshold is a random variable μ_i drawn independently from a probability distribution with support [0, 1]. The associated multivariate probability density function for all the nodes in the graph is $f_1(\mu)$. The cost threshold profile of agents is $\mu := (\mu_i)_{i \in V}$.

- A social threshold for agent i is a random variable θ_i drawn independently from a probability distribution with support [0, 1]. The multivariate probability density function for all the nodes in the graph is $f_2(\theta)$. We define the social threshold profile of agents as $\theta := (\theta_i)_{i \in V}$.

As mentioned, we assume that agents' thresholds are randomly and independently drawn from uniform probability distributions as the government has no reason to believe that some thresholds are more likely than others (Kempe et al., 2003; Lim et al., 2016). Then, a network $G_{\mu,\theta}$ is a graph endowed with the two profiles of thresholds.

Let C_t be the cost function of the technology at time t, bounded between [0, 1]. This property ensures the matching between the cost function and corresponding agents' thresholds μ_i. To introduce the learning characteristics, we assume α to be a technological learning effect on the cost function. As a result, shapes of the cost curve will follow a decreasing and convex trend (matching cost trajectories observed for some renewables (e.g. solar PV)). We then evaluate the effect of learning on diffusion by discretizing α over different constant rates (i.e. [0.1; 0.3; 0.5; 0.7]).[4] This allows us to capture the relationship between technological learning and diffusion. In our setting, α is bounded between [0, 1] - meaning that the cost of the technology decreases from 1 to 0 with respect to the number of adopters S. That is :

$$C_t = C_0 \times (| \cup_{\tau=0}^{t-1} S_\tau |)^{-\alpha}$$

2.2.2 Conditions for switching

We now consider dynamics of diffusion cascades in a network $G_{\mu,\theta}$. The binary state of agent i at time t is denoted $x_i(t) = \{0, 1\}$, referring to off and switched. The set of additional switches in network G at time t is defined as $S_t(G_{\mu,\theta})$. To launch the process of diffusion, we assume the government to seed a random set of agents with the technology at time $t = 0$. This subset of agents is denoted as $S_0 \subseteq V$, at t_0. Then, at $t = 1$, any agent $i \in V \setminus S_0(G_{\mu,\theta})$ will switch, i.e., $i \in S_1(G_{\mu,\theta})$ if

$$|C_t(S_0(G_{\mu,\theta}))| \leq \mu_i, \qquad \text{and} \qquad \frac{|S_0(G_{\mu,\theta}) \cap N_i(G_{\mu,\theta})|}{|N_i(G_{\mu,\theta})|} \geq \theta_i.$$

This means that at $t = 1$, agents switch only if the cost of the technology is lower than their respective threshold μ_i and if the proportion of their neighbors having adopted exceeds their threshold θ_i. This hypothesis matches the literature on innovation diffusion and complex contagion in networks (Delre et al., 2007; Beaman et al., 2018). Then, for a given period $t \geq 0$, node $i \in V \setminus \cup_{\tau=0}^{t-1} S_\tau$ will switch at t, i.e., $i \in S_t(G_{\mu,\theta})$ if

$$\textbf{(1)} \quad |C_t(\cup_{\tau=0}^{t-1} S_\tau(G_{\mu,\theta}))| \leq \mu_i, \quad \text{and} \quad \textbf{(2)} \quad \frac{|\{\cup_{\tau=0}^{t-1} S_\tau(G_{\mu,\theta})\} \cap N_i(G_{\mu,\theta})|}{|N_i(G_{\mu,\theta})|} \geq \theta_i.$$

Eq.**(1)** and Eq.**(2)** represent the necessary conditions for switching. This means that any agent who has not switched by some period t, switches in time period $t + 1$ if the cost of the technology falls below his threshold μ_i and if the proportion of his

[4] We relegate extreme scenarios α={0;1} to the Appendix, Section 1.1.

neighbors who switched is greater or equal to his threshold θ_i. In other words, there is a reinforcing feedback : the more agents adopt, the more the cost decreases leading to more agents to adopt in the subsequent period. This pattern has been observed for clean technologies such as solar PV (Farmer et al., 2019). For a given $G_{\mu,\theta}$, define the fixed point of the process such that :

$$S_0(\mathrm{X}) = S(G_{\mu,\theta},\, S_0) \longrightarrow S_t(G_{\mu,\theta}) = \emptyset \text{ for all } t > 0.$$

2.2.3 Expected size of switches

Although not implemented in the following sections, we can estimate the expected average size of the resulting cascade of switches from $f(\mu, \theta)$, separable into two independent and non-correlated probability density functions $f_1(\mu)$, $f_2(\theta)$ (cf. Lim et al., 2016). For a given graph G and S_0, we can map the realization of $f(\mu, \theta)$ to a set of switches $S(G_{\mu,\theta},\, S_0)$ and treat $S(G_{\mu,\theta},\, S_0)$ as a random variable with a probability distribution $f(\mu, \theta)$, keeping into account the cost rule.

Therefrom, we compute the expected probability of any particular agent i switching, given a seeded subset of agents S_0, by taking the expectation with respect to $f(\mu, \theta)$:

$$P_i(G, S_0) = \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} |S(G_{\mu,\theta}) \cap \{i\}| f(\mu, \theta) d\mu d\theta$$

Then, the expected number of switches in graph G when S_0 is defined is :

$$E[S(G, S_0)] := \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} |S(G_{\mu,\theta}, S_0)| f(\mu, \theta) d\mu d\theta = \sum_{1}^{n} P_i(G, S_0)$$

3 General results and Analysis

3.1 Preliminaries : Numerical Setting

We consider a population of N=100 agents with n=10 connections per agent.[5] Agents are placed on three distinctive graphs created according to the Watts Strogatz algorithm (1998).[6] The network is fixed throughout a simulation run. Each agent is endowed with two thresholds profiles μ_i and θ_i, drawn independently from a uniform probability distribution with support [0, 1]. At t_0, we set the number of initial seeds $S_0 \in$ [0,..., 100], randomly selected, to launch the cascade process. We test this approach on four learning effects scenarios where α takes the respective values [0.1; 0.3; 0.5; 0.7].[7] In each single history, we randomized the agents in the seed set and the associated thresholds allocation. Resulting cascade follows the dynamics exposed in Section 2. This framework guarantees that the process eventually stops. To examine the considered graphs, we set for every edge - following the Watts Strogatz algorithm described above - the rewiring probability p to [0; 0.1; 1]. For each p value, 1000 different graphs are created and on each graph a single history is run. For lattice networks (p=0), note that the structure of the network remains unchanged between simulation runs (i.e. only thresholds and seeds vary).

We are interested in evaluating how diffusion processes in lattice, small-world and random networks, where clustering ranges from high to low levels. To this end, we examine the average number of aggregate adopters, length of cascades as well as speed of adoption convergences. Such a macroscopic perspective brings insights on the role of clustering, path length and learning in diffusion propagation. In the remainder of the paper, the curves provided are averages over 1000 replications and presented for each class of networks. We expose the number of aggregate final adopters, associated

[5] Although social networks are sparse, meaning they exhibit fewer links than the possible maximum number of links within that network (Hu and Wang, 2009), such framework is common in the literature on complex social networks (Cowan and Jonard, 2004; Zhaoyang et al., 2018; Snellman et al., 2019).

[6] cf. Section 2.1 for description.

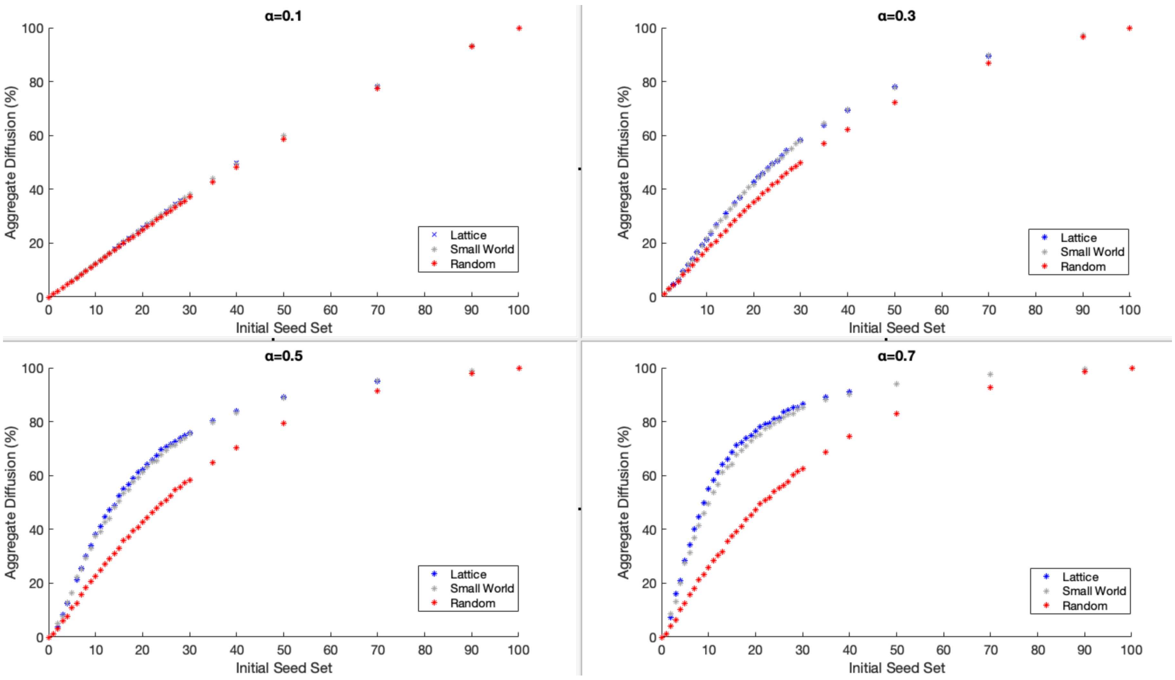
[7] cf. Appendix, Section 1.1 for α={0;1}.

times of convergence as well as resulting cascades process per period. With respect to times of convergence and per period cascading processes, we only show relevant results (S_0=[5; 35]) for clarity of presentation.

3.2 Understanding diffusion (I) : Seed set and Learning effects

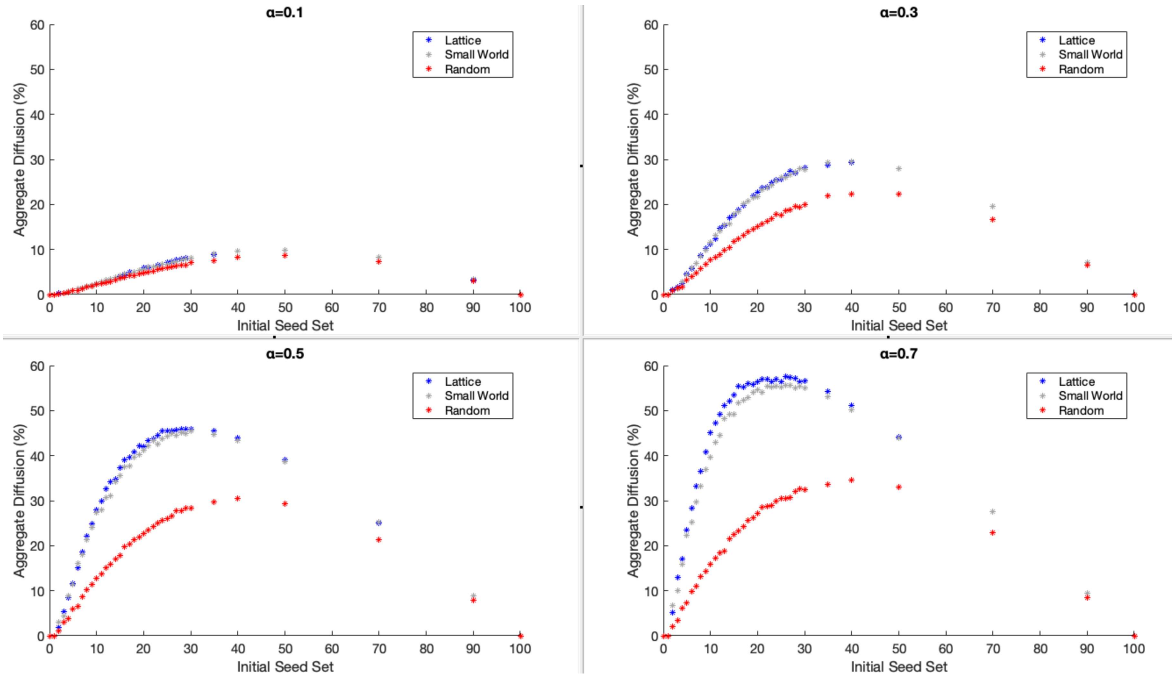
For lattice, small-world and random networks, Figure 1.3 and Figure 1.4 hereafter exhibit the relationship between initial seed set S_0 and average aggregate diffusion under four scenarios of learning (i.e. α=[0.1; 0.3; 0.5; 0.7]).

Figure 3: Aggregate diffusion as a function of initial seed sets



Overall, aggregate diffusion in the non-seed population (cf. Figure 1.4) is a non-monotonic function of S_0, concave where the function equals zero at extremes [0; 100] (i.e. when S_0=[0; 100], the diffusion is either null or full). A peak in resulting diffusion (i.e. after seeding) is observed when S_0 lies somewhere between 24% and 50% (cf. Fig.1.b.). Precisely, for each network configuration, minimum diffusion peaks occur when α=0.1 (e.g. when S_0=50, diffusion reaches 9% of adopters in random networks) while maximum peaks are observed when α=0.7 (e.g. approximately 57% final adopters for 26% initial agents seeded in lattice and small-world networks).

Figure 4: Aggregate diffusion as a function of initial seed sets (non-seed population)



With respect to clustered structures, results suggest that the more learning rate increases, the larger the cascade is, and the lower the amount of the initial seed set needs to be to reach high levels of spreading. This feature is captured by the following : increasing the learning effect fosters the impact of one agent adopting on the technology cost function. In other words, with higher rates of learning, fewer new adopters are required to reach an equivalent decrease in the cost function. Therefrom, a faster drop in technology cost leads to a larger scope of agents whose thresholds μ_i is crossed (for the same amount of initial seeds). The latter suggests that aggregate diffusion and learning rates are intertwined with one another. To better investigate this feature, we map in the Appendix (Section 2.4) aggregate diffusion in a one threshold scenario (social effect). Interestingly, results reinforce our findings. In a model only based on neighborhood influence, diffusion reaches higher levels in the non-seed population (e.g. for 20 initial seeds, diffusion in the non-seed population reaches 67 agents in clustered networks and 33 in random networks). Then, adding a cost threshold contains the dynamics of adoption and increasing the learning parameter allows the technology to percolate as the cost condition (1) is more easily met in the set of agents (cf. Section 2.2). Overall, the higher the learning parameter is, the closer to a one threshold scenario diffusion levels stand. This observation is particularly relevant for policy makers as the choice of the technology to support and its associated learning dimension have a great influence on diffusion dynamics.

From a network approach, the aggregate amount of final adopters differs in every scenario. Indeed, lattice and small-world networks, both exhibiting high levels of clustering, perform better than random networks, whatever the levels of learning and initial seeds - except extremes (i.e. S_0=[0; 100]). Moreover, as the learning parameter grows, the diffusion gap[8] between clustered and random networks gets larger, embodying the strong influence of learning and the critical role of clustering in diffusion. As an example, for S_0=24 and α=0.7, diffusion levels achieve nearly 81% in clustered networks while in random networks, technology propagates to less than 54% of agents. This result matches previous researches on complex contagion diffusion in networks, suggesting that clustering is critical for innovation spreading (Centola and Macy, 2007). Following the recent work of Centola on complex contagion (2018), we assume the process of technology diffusion to start out locally, then spilling over to nearby neighborhoods, and ultimately percolating through the population of agents. Overall, our results suggest that clustered structures and learning effects favour the adoption of a technology subject to learning. These networks exhibit higher diffusion levels compared to dynamics examined in random networks.

Considering small-world networks, technology tends to diffuse a bit lower than in lattice structures (cf. α=[0.5; 0.7]). Here, one can assume that differences between small-world and lattice networks explain this observation. Although exhibiting high

[8]cf. Appendix, Section 2.1.

level of clustering, small-worlds are less clustered than lattice structures - due to some short paths crossing the whole network (cf. Section 2.1). Hence, we can treat small-worlds as halfway structures between lattice and random networks. In this case, a lower clustering coefficient explains the relative underperformance of small-worlds compared to lattice networks. Again, note that the largest diffusion gap between clustered and random networks is observed when the learning effect is the highest (α=0.7) for an initial seed set fixed at 13%. We conclude that parameter α drives the diffusion and associated adoption gaps between considered networks.

3.3 Understanding diffusion (II) : Cascades' spreading

We are now interested in evaluating the heterogeneity of diffusion with respect to networks. We base our analysis on the variance of diffusion rate between models run as it represents a natural measure of dispersion (Cowan and Jonard, 2004). Remember, our results are averages over 1000 numerical replications. Moreover, studying how cascades spread is relevant for questions related to policy design and associated outcomes' uncertainty. Figure 1.5 reports the variance of aggregate diffusion as a proxy for heterogeneity. Interestingly, heterogeneity and diffusion behave in a similar manner. In every scenario, a peak in heterogeneity is observed for both examples of clustered networks, displaying highest levels of disparity in cascades outcomes. Heterogeneity increases as a function of learning with larger ranges for clustered networks (e.g. for S_0=7 and α=0.7, aggregate diffusion variance in lattice, small-world and random equal 567, 522 and 92 respectively). Moreover, in lattice and small-world networks, an increase in learning leads to fewer initial seeds required to reach highest levels of variance (as observed for aggregate diffusion).

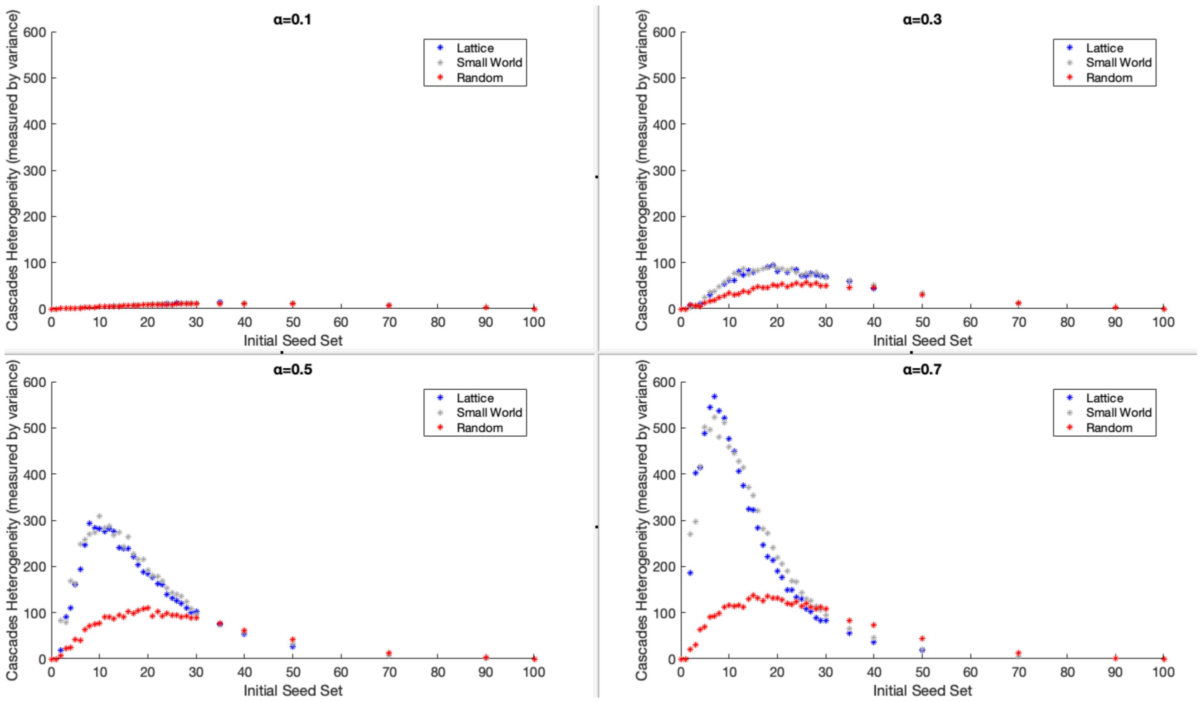
To gain more qualitative insights on this issue, we also map heterogeneity in the case of a one threshold scenario (θ_i).[9] We observe that in the absence of a cost threshold, heterogeneity decreases as a function of initial seeds in clustered networks. In

[9] cf. Appendix, Section 2.4.

our scenarios, as noticed for aggregate diffusion, an increase in learning brings levels of variance and diffusion closer to the ones observed in a one threshold setting (θ_i) - highlighting again the critical effect of learning parameters. Moreover, in a two-threshold setting, variance increases to reach highest peaks associated with highest levels of diffusion while in a one threshold model, variance decreases as a function of initial seeds. We conclude that adding a second condition to adoption (i.e. cost threshold) also has a strong impact on heterogeneity in clustered networks compared to a one threshold configuration. For random networks, diffusion and heterogeneity follow the same pattern in the two designs.

To provide some perspectives to our results, levels of heterogeneity observed in clustered networks refer to the percolating process. As exposed, the diffusion starts out locally, then spreads to nearby neighbors, and ultimately percolates through the network. This process tends to be subject to a clear "rigidity" in terms of diffusion dynamics. On the one hand, if diffusion percolates, it reaches high levels of global spread; on the other hand, if it does not propagate in the initial clusters (i.e. where the initial agents are seeded), diffusion is capped to a low number of adopters. In random networks, the process is smoother as short path lengths do not contain or exacerbate diffusion. These observations complement researches on seeding strategy and percolation in networks. As Acemoglu (2011) developed, diffusion in clustered networks requires at least one initial seed among clustered groups to make percolation in the whole neighborhood possible. Here, heterogeneity of our aggregate diffusion results reinforces this view - that technology only "diffuses" in random networks while in clustered networks, diffusion is exacerbated to one extreme or another (i.e. low or high level). From a policy perspective, this observation is critical. Indeed, it suggests a possible trade-off between maximising adoption and uncertainty in results. Namely, where aggregate diffusion levels are the highest, dispersion is the largest. If there is a strong connection between diffusion and network structures, this may indicate a policy tension : targeting diffusion levels with lower expected variability or favouring maximum adoption with more uncertainty in terms of final results. Because uncertainty is critical for public policy design, this observation calls for a different policy approach with respect to the objective targeted. In the context of climate change, this dimension is critical as public policies tend to implement strategies dealing with peer effects and social influence. Designing policies aiming at targeting clustered network (e.g. cooperatives of farmers) does not imply that diffusion will be successful. Then, to limit variability in results, economic instruments targeting a specific class of agents could be implemented to allow the technology to percolate within groups. Such perspectives are discussed in conclusion of this work (Section 4).

Figure 5: Diffusion heterogeneity measured by variance

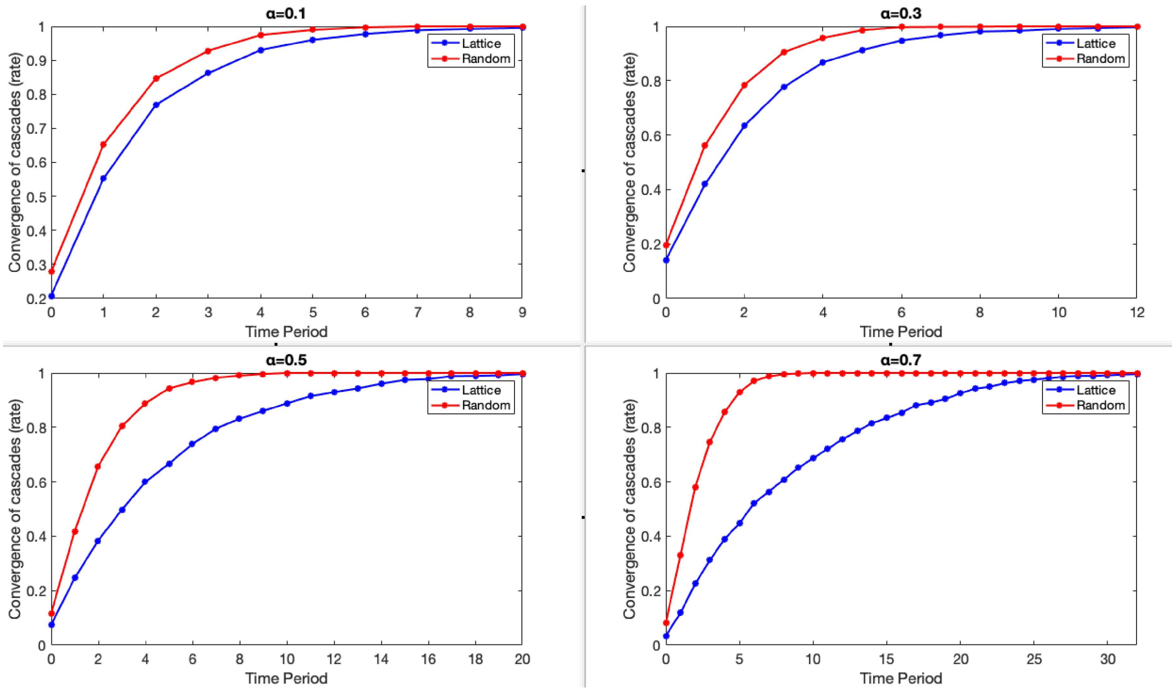


3.4 On Cascades' lengths and Adoption dynamics

To this point, our evaluation has focused on aggregate diffusion properties. We now turn to the transitory analysis of the model. The speed at which the technology diffuses is a major policy concern, especially for technologies aiming at reducing greenhouse gases emissions (IEA, 2018). Here, we address this issue and examine how spreading dynamics is affected by network structures. We name "time of convergence" the number of time periods required for a cascade process (i.e. a simulation) to stop. For ease of presentation, we only consider lattice and random networks as small-world configurations mimic lattice curves in our results. Indeed, in our two-threshold model, clustering tends to overcome path length dimension in diffusion dynamics in the small-world configuration. This outcome was expected as high levels of clustering favour diffusion (see Centola (2018) for a review). In addition, we focus on scenarios where S_0=[5; 35][10] as they exhibit the main interesting outcomes.

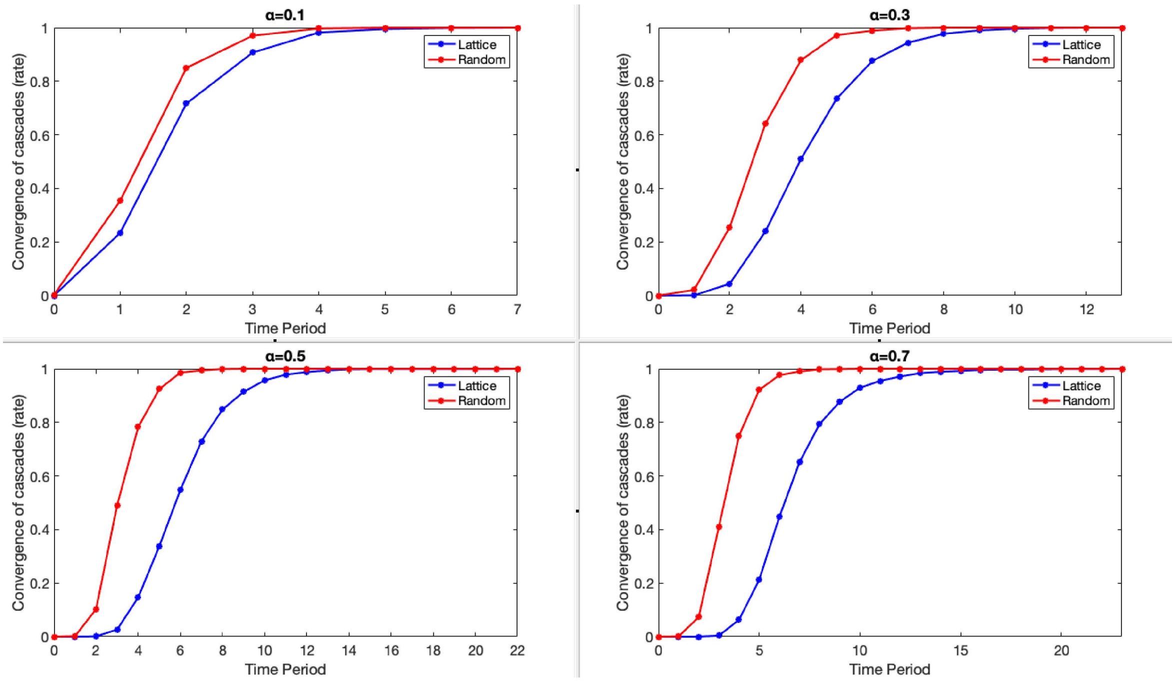
Then, Figure 1.6 and Figure 1.7 show the relationship between the total amount of simulations (i.e. 1000) in percentage and the associated speed of convergence, reported up to 32 time periods.

Figure 6: Rate of Cascades convergences as a function of time, $\boldsymbol{S_0=5}$



[10] cf. Appendix, Section 2.3 for other scenarios.

Figure 7: Rate of Cascades convergences as a function of time, $\boldsymbol{S_0=35}$



As a reminder, random networks have little local structure and short paths connecting agents. In this case, simulations converge faster after the launch of the process. Precisely, at least 70% of simulations have converged at t$\leq$4 in most scenarios, reaching relatively low levels of aggregate diffusion. For lattice networks, early diffusion tends to spread slower than in random networks (e.g. at t$\leq$4, some scenarios exhibit rates of convergence lower than 5%, cf. α=0.7, S_0=35). But the process continues longer, and reaches higher levels of aggregate diffusion.

Again, note that the learning parameter α influences cascades' lengths. Indeed, increasing its effect leads to, in most cases, additional periods to converge, whatever the level of initial seeds. When α=0.7, speeds of convergence in lattice networks are the slowest observed for each period, in every scenario. By matching this observation with aggregate number of adopters, we suggest that lower times of convergence stem from a larger scope of agents whose thresholds θ_i are crossed. The latter induces a longer and higher adoption dynamics in clustered networks.

We also observe that a larger initial seed set combined with high values of learning leads to S-shaped curves for cascades' convergences. In other words, once a period threshold is crossed, cascades tend to stop processing (cf. α=0.7, S_0=35). In order to strengthen our claim, we map in Figure 1.8 and Figure 1.9 (at the end of this section) the associated times of convergence with respect to aggregate amount of adopters at each period for S_0=[5; 35]. This approach sheds light on two key aspects. First, diffusion dynamics in lattice and random networks share common features as regards speed and aggregate diffusion. For $S_0 \leq 35$, in early periods ($t \leq 3$), they perform equivalently regarding final aggregate diffusion. Second, when the process converges in random networks, diffusion in clustered structures propagates to reach higher levels, increasing the length of the cascade. This observation confirms our previous expectations.

Overall, if our results suggest that high diffusion is coupled with clustering, we found out more heterogeneity (i.e. variance) in cascades propagating in these networks. Following our findings on cascades lengths, it might not be relevant for policy makers to favour clustered structures if the amount of diffusion targeted is low. The latter confirms previous researches suggesting that for low levels of seeds and small values of t, networks exhibiting a low degree of clustering might diffuse the innovation further (Acemoglu et al., 2011). However, when it comes to large spread of technologies subject to learning, clustering performs better. Adding up to these results, the next section evaluates the relevant government strategy in terms of initial seeds to efficiently maximize diffusion in networks examined.

Figure 8: Adoption dynamics as a function of time, $\boldsymbol{S_0=5}$

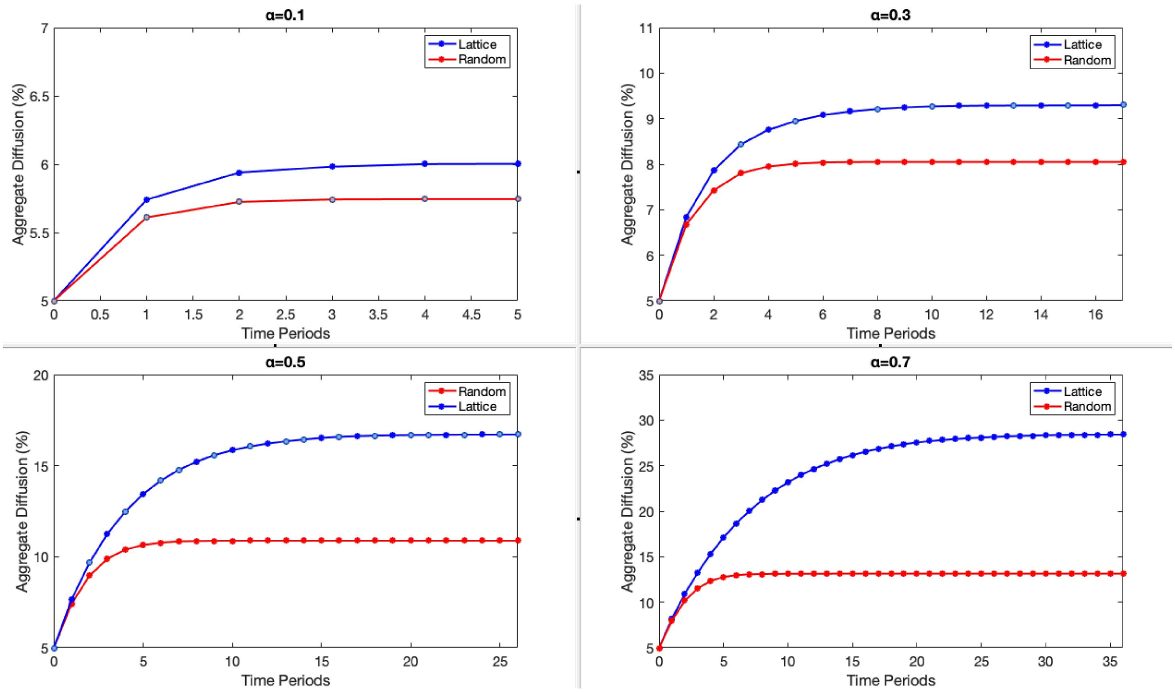
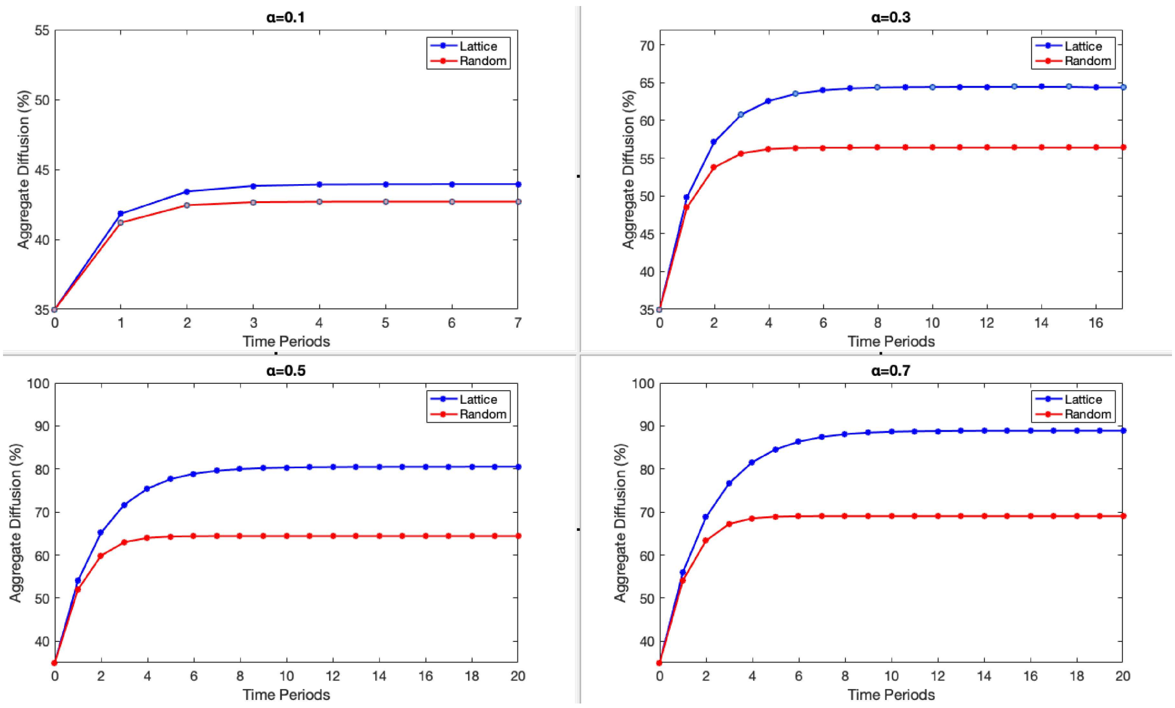


Figure 9: Adoption dynamics as a function of time, $\boldsymbol{S_0=35}$



3.5 Efficient Strategy : Tipping Points in Seeding

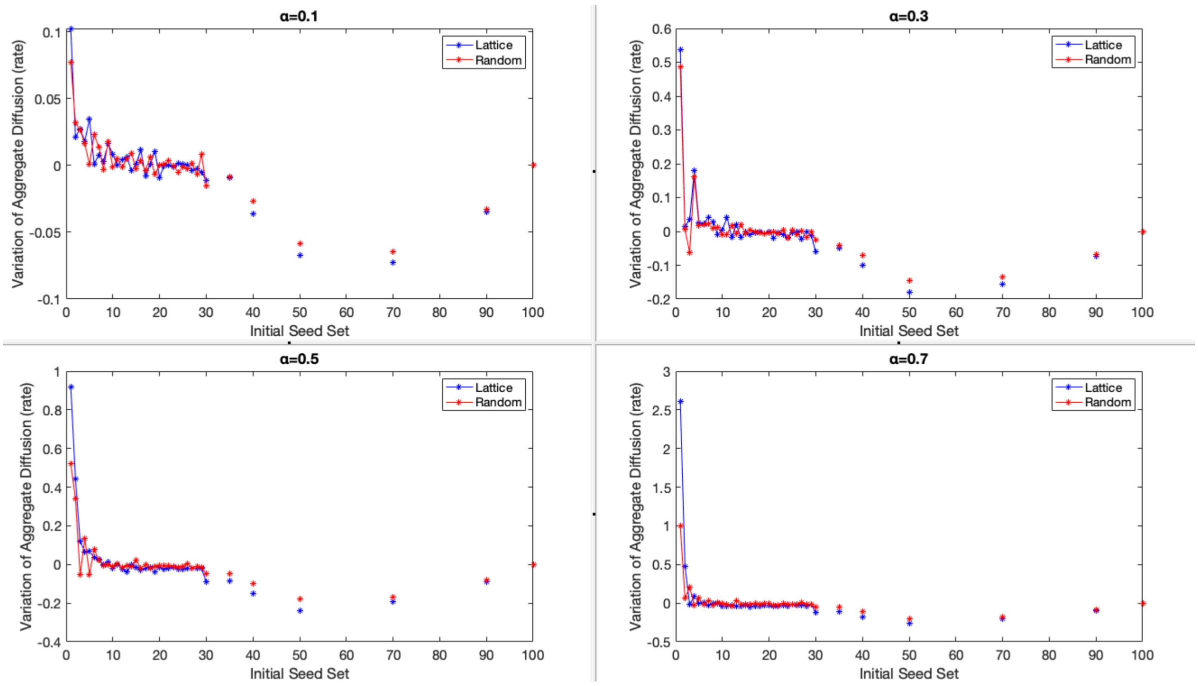
From a government perspective, maximizing or limiting the spread of diffusion comes with a cost of action (e.g. number of seeds in our case). These issues have been largely documented in the literature (Kempe et al., 2003; Akbarpour et al., 2018). In the context of climate change, deploying environmental-friendly technologies at least cost is a key objective for governments - already subject to public debt. In our framework, a cost efficient strategy for a public intervention would be to set the level of initial seeds (i.e. cost) such that it maximizes final aggregate adoption. In other words, maximizing the ratio between aggregate diffusion and initial seed set, in which seeding one supplementary agent leads to a larger effect on aggregate diffusion. By investigating the issue of marginal seeding, we complement our previous policy outcomes on the role of learning and network structures in diffusion. Indeed, an increase in the learning parameter leads to larger diffusion and to lower associated amounts of seeds required (i.e. in clustered networks). From a government perspective, this suggests that it could be inefficient to target high amounts of initial seeds to reach high levels of adoption. If this result is critical, it fails to precisely evaluate the impact of seeding one supplementary agent (i.e. cost) on aggregate diffusion.

To address this question, we map in Figure 1.10 below the marginal change of aggregate diffusion divided by the number of seeds in lattice and random networks (i.e. high and low clustered structures). If the corresponding value is positive, seeding the associated amount of agents is beneficial for diffusion. In other words, an additional seed leads to more than one additional adopter. On the contrary, a negative value suggests that the size of the seed set outweighs the final diffusion benefits (i.e. adopters), even if diffusion still increases (note here that it remains optimal to seed at a rate indicated by the peak observed in Figure 1.4). Here again, we focus our analysis on lattice and random structures as small-world mimic lattice structures).

From Figure 1.10, we note that the learning parameter has two main effects :

first, moving from low to high levels of learning decreases the angular variation pattern observed. Second, higher learning parameters lead to a smaller amount of initial seeds subject to positive ratio values.[11] Overall, the level of initial seeds having positive values is always lower in clustered networks compared to random networks which makes a government intervention (i.e. seeding) less costly in these configurations. The latter matches previous observations on the impact of the learning parameter on diffusion in clustered networks - namely, higher learning effects lead to larger diffusion with lower amount of initial seeds required to reach maximums.

Figure 10: Marginal change of aggregate diffusion divided by the number of seeds



4 Conclusion

For some types of technologies, the cost of a unit decreases exponentially over time. As for hardware technologies, green technologies like solar PV follow this trend (Farmer

[11]Note : here we report associated seeds above which we observe no more positive values : when $\alpha = 0.1$, negative values arise when S_0=25 (lattice), S_0=29 (random); when α=0.3, negative values appear when S_0=14 (lattice) , S_0=25 (random); when α=0.5, negative values arise when S_0=10 (lattice), S_0=15 (random); when α=0.7, negative values arise when S_0=7 (lattice), S_0=14 (random).

and Lafond, 2016). We have shown that under a complex contagion approach, the spreading of these technologies is clearly affected by the structure of the social network over which it takes place. In the context of global warming, these findings are critical as public policies aim at maximising their deployments by implementing economic incentives (e.g. subsidies). In this paper, we provide clear evidences that under a particular diffusion process (i.e. contagion), clustered organizations are critical to spread a technology. By adding a cost dimension, we innovate with respect to previous researches on epidemic diffusion in networks and gives practical insights to policy makers. Among those, targeting clustered organisations (e.g. favouring cooperatives of farmers in agriculture (Viardot, 2013)) comes at a cost : greater uncertainty in global adoption outcomes. This is the very old efficiency versus uncertainty trade-off. When network structures result in a high average aggregate diffusion rate, they also generate higher variances. That is, the distribution of cascade results is relatively variable. To the extent that efficiency in policy implementation remains a governmental concern and if diffusion of technologies is considered as a key input to develop regions - and ease global warming-, policies aimed at inducing efficient diffusion will have to address the consequent uncertainty in results. But whether or not this concern is real depends on the measure used — if variance is the appropriate measure of distribution, there is a real problem. As exposed, the impact of learning rates - on associated cost function - remains critical for spreading. In this context, the choice of the technology to promote is of great importance for the design of effective policies (e.g. case of renewables).

Practically, to target clustered structured, government should be aware of underlying social networks in the selected population. On this issue, the growth of social platforms and the associated increasing amount of data (e.g. social, geographic, consumption) could help capturing underlying social structures and would provide powerful informations for policy makers. For instance, one objective could be to increase the social exposure of an agent to clean products by targeting agents in her social neighborhood. On this issue, a recent study based on PV adoption data demonstrated the contagious feature of such a technology (Baranzini et al., 2017) while the use of facebook data has already been explored to capture the diffusion of epidemics across agents (Kuchler et al., 2020). For the specific case of agriculture, the role of cooperatives to diffuse knowledge and technology has been pointed out over the last decade (Joffre et al., 2019). In this field, governments could design adoption incentives relying on membership data of cooperatives to increase likelihood of adoption. Overall, our model paves the way to applications using such data.

From another perspective, if the underlying network is estimated, mapping the contagion of a technology in a network of agents could give an estimate of the potential future cost of the technology. By doing so, policy makers could evaluate the learning parameter of the technology as it is a key determinant for diffusion. However, reaching this objective depends on first periods of diffusion (i.e. launch of the process). Then, governments should promote key technologies able to reach a certain amount of adoption. The learning dimension is a critical aspect to deploy green technologies (e.g. PV, wind turbine) and tackle climate change.

Finally, policy makers could limit uncertainty in results in cluster structures by giving access to the technology to agents less able to afford such a product. Indeed, those agents, exhibiting a low cost threshold (i.e. they cannot afford the technology if the latter does not diffuse massively), are hampering the diffusion as they are not adopting the product. By implementing economic mechanisms to support such population to adopt, diffusion would be less subject to heterogeneity and could reach higher levels. Such policies would allow a large share of the population to adopt the technology, creating feedback effects for the rest of the population.

With respect to our model, it could be extended in several obvious ways. We have taken the network structure as given, and have examined its effect on the diffusion process. Apart from paving the way to applications in the field of technology adoption and diffusion, our model could be extended by investigating relevant economic questions. Indeed, we exposed the impact of learning on diffusion and the associated cost function but we did not investigate the optimal decreasing path of the cost function with respect to threshold distribution. This approach would bring insights on how should a cost decrease behave. In the wake of network science analysis, some studies would be valuable to apprehend the impact of degree distribution on general diffusion under a two-threshold approach. The latter would fill the gap in the literature and would allow some comparisons with other complex contagion problems. In terms of modelling, other models of diffusion could also be implemented such as the Independent Cascade Model (ICM). This could bring some relevant comparisons in terms of outcomes. Finally, in the model in this paper, there is no innovation, only diffusion after a government random seeding action (which is proven to not be the most effective (Singh et al., 2013)). Questions related to the centrality of agents in networks and their potential cascading powers are relevant to explore, especially if some are to be characterized as innovators. Overall, our model could be implemented to real cases of technology diffusion (e.g. energy technologies exhibiting experience curve patterns).

Appendices of Chapter 1

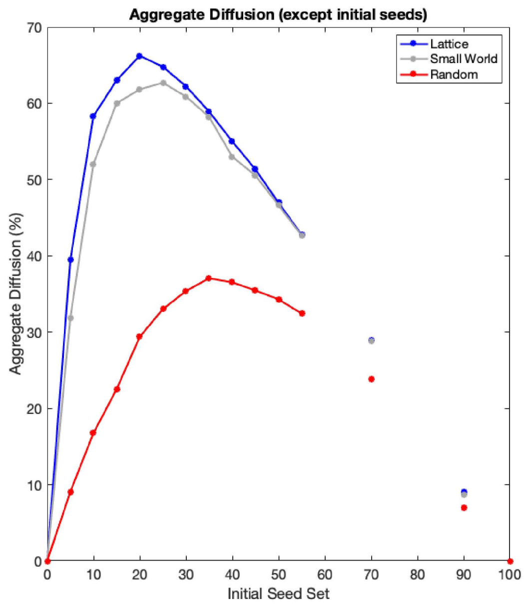
1.1 Aggregate diffusion and variance, α=[0;1]

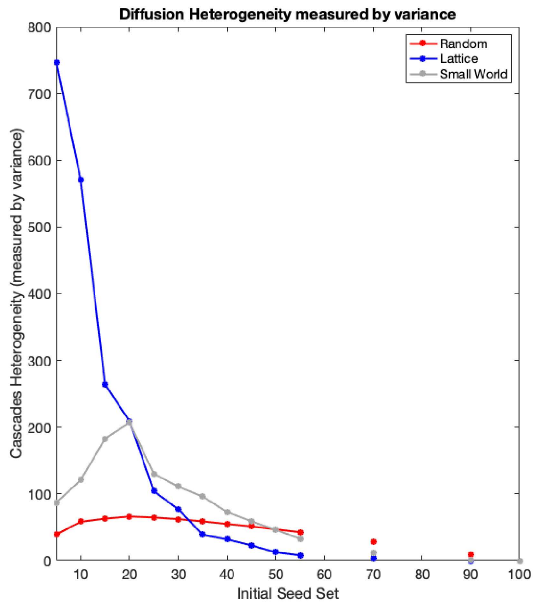
1) For α=0, the cost function is :

$$C_t = C_0 \times (|U_{\tau=0}^{t-1} S_\tau|)^{-0} = 1$$

whatever the initial seed set. Then, we observe no diffusion in networks at all as the cost remains too high.

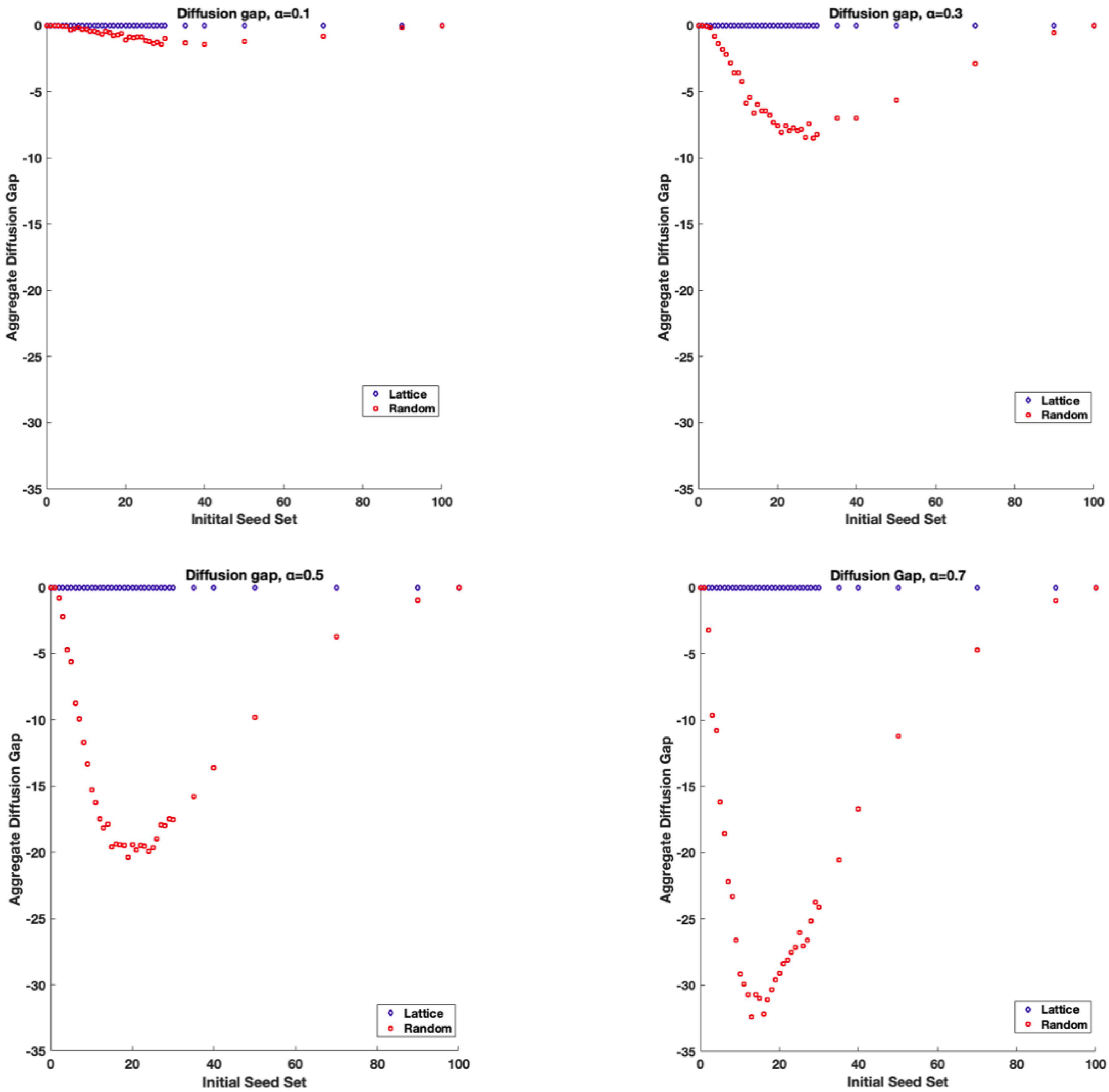
2) For α=1, we have (for steps of 5 seeds):





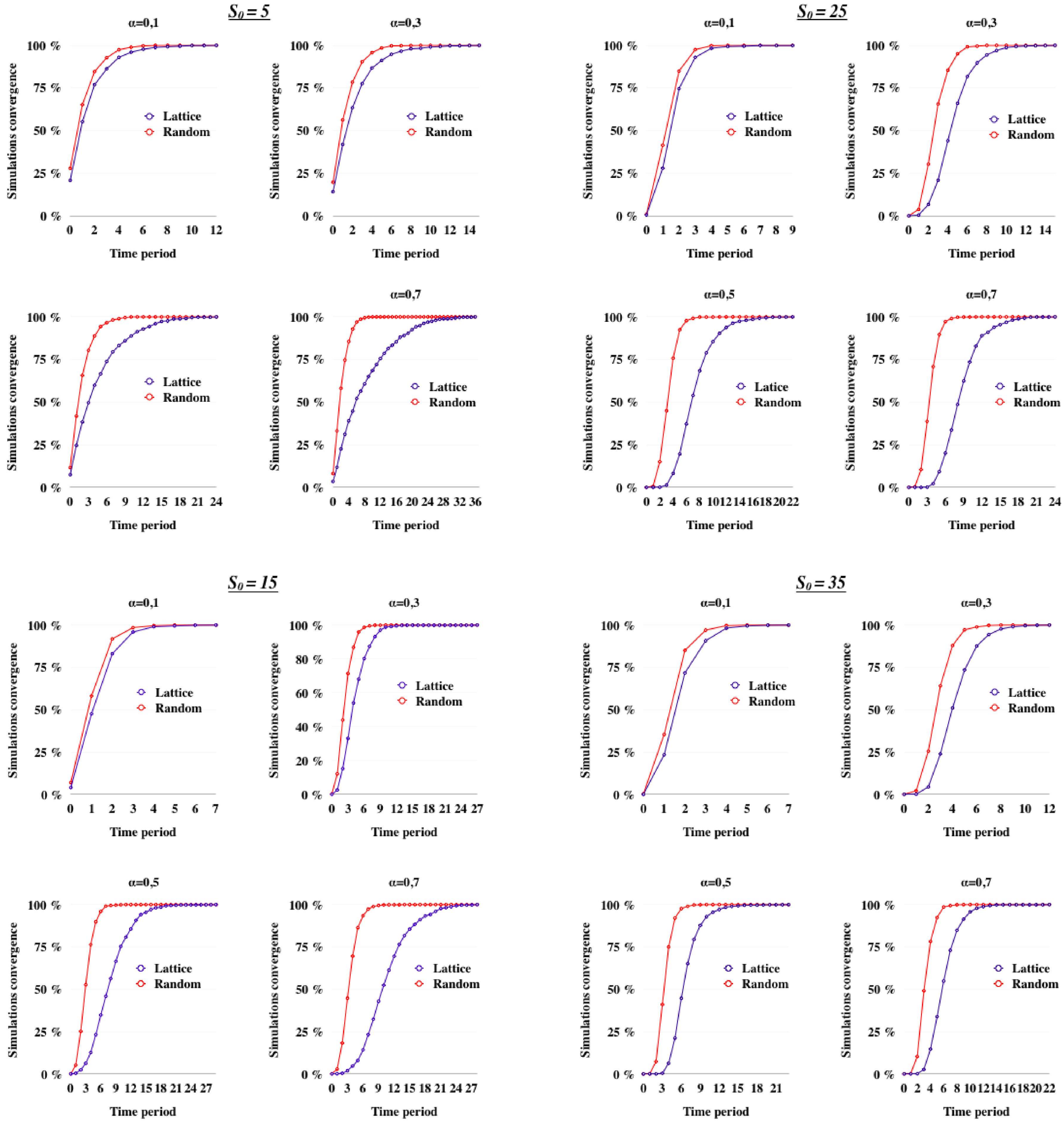
2.1 Diffusion gaps

Figure 11: Diffusion gaps, baseline lattice



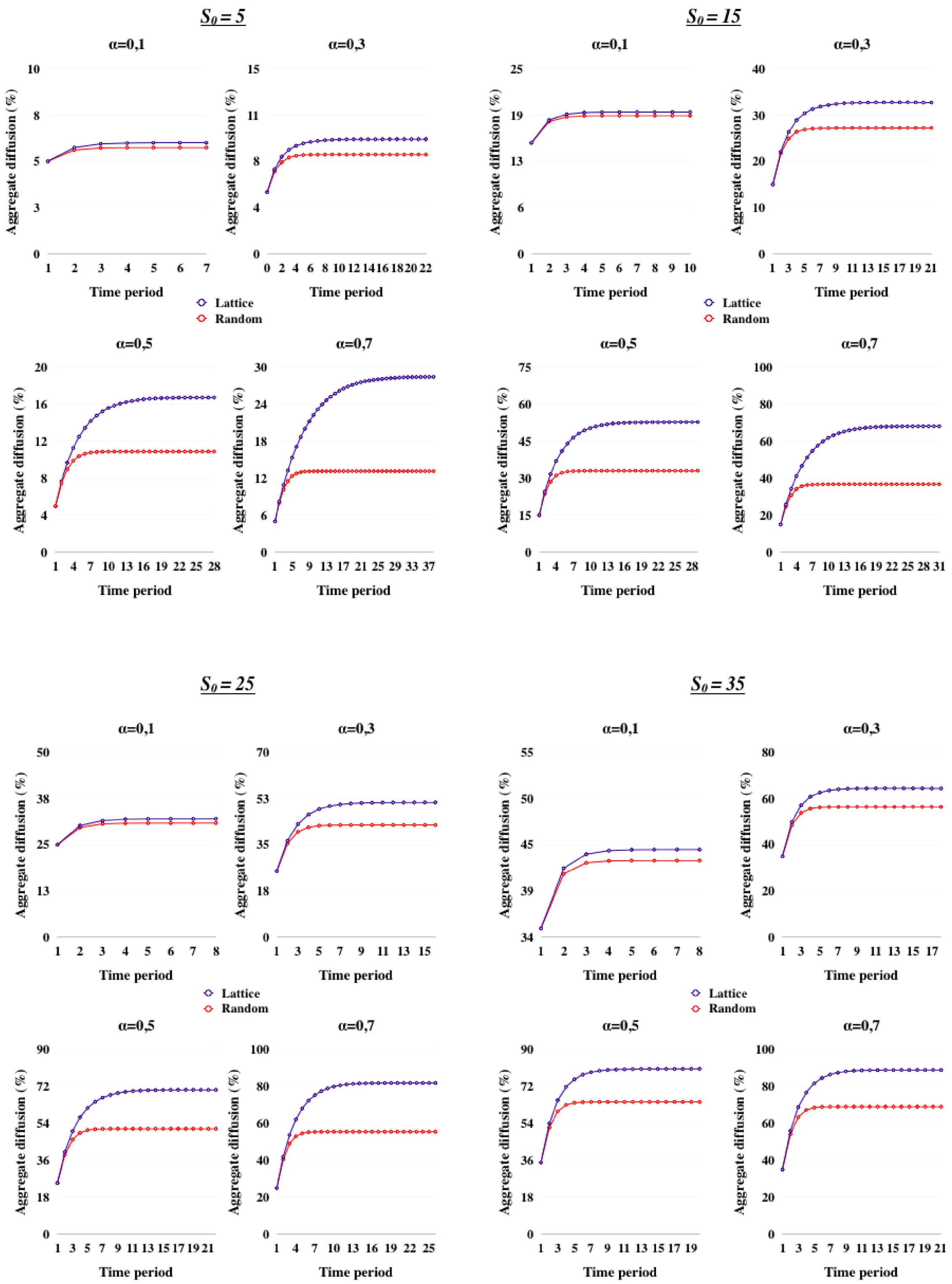
2.2 Cascades convergences

Figure 12: Cascades convergences, S_0=[5; 15; 25; 35]



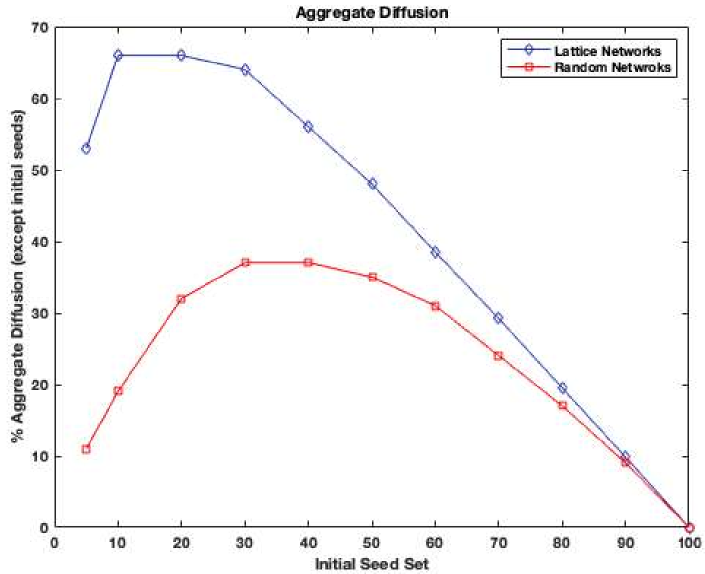
2.3 Adoption convergence

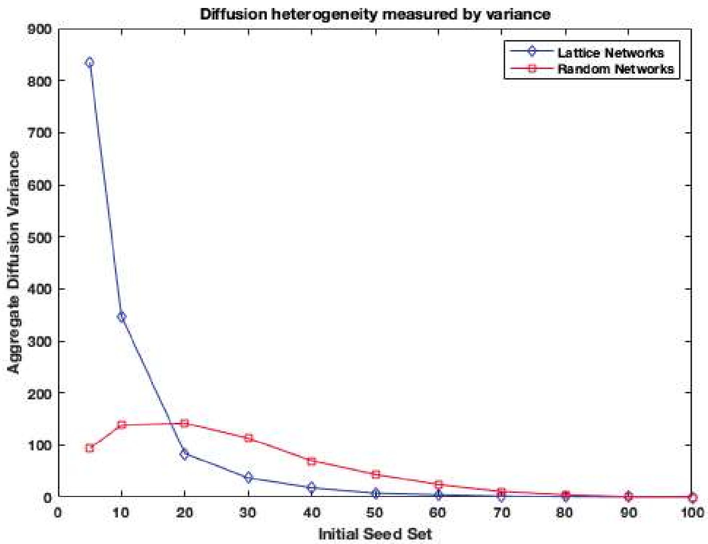
Figure 13: Adoption dynamics with respect to time, S_0=[5; 15; 25; 35]



2.4 One threshold scenario θ_i

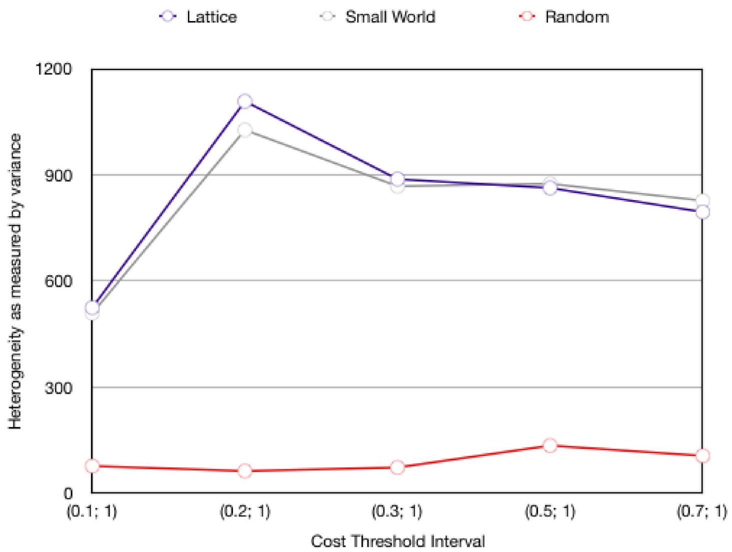
Figure 14: Aggregate diffusion (except initial seeds) and heterogeneity in a one threshold scenario (neighborhood effect without cost dimension)

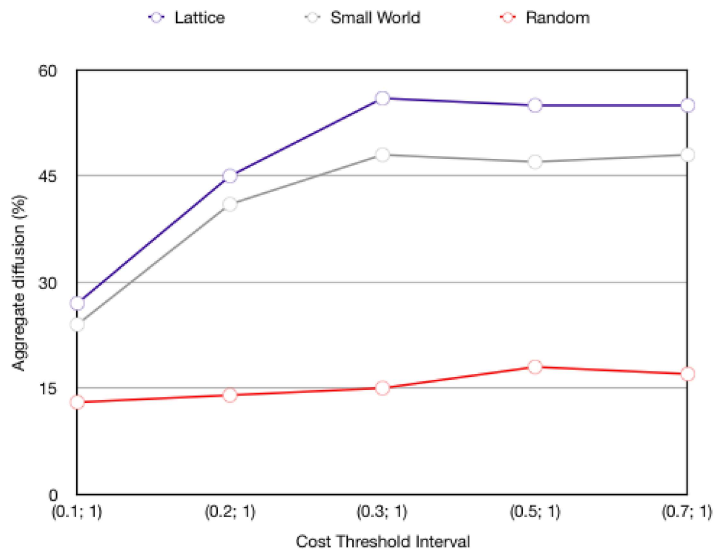




2.5 Variation in cost threshold distribution

Figure 15: Aggregate adoption and heterogeneity for different scenarios of cost threshold distribution over specific intervals (0,1;1); (0,2;1); (0,3;1); (0,5;1); (0,7;1), with S_0=[5]





2.6 Robustness check : Number of connections per agent & Aggregate diffusion

2.6.1. For S_0=[5]

Table 1: *n=5*

Learning effects α	Lattice	Small-World	Random
0.1	6	6	6
0.3	10	9	7
0.5	18	15	9
0.7	36	26	10

Table 2: *n=20*

Learning effects α	Lattice	Small-World	Random
0.1	6	6	6
0.3	9	9	8
0.5	15	13	11
0.7	26	23	12

Table 3: *n=30*

Learning effects α	Lattice	Small-World	Random
0.1	6	6	6
0.3	9	9	7
0.5	15	14	10
0.7	23	22	16

Table 4: *n=40*

Learning effects α	Lattice	Small-World	Random
0.1	6	6	6
0.3	9	9	9
0.5	15	16	14
0.7	21	22	19

2.6.2. For S_0=[35]

Table 5: *n=5*

Learning effects α	Lattice	Small-World	Random
0.1	44	43	42
0.3	65	64	61
0.5	81	81	58
0.7	92	89	59

Table 6: *n=20*

Learning effects α	Lattice	Small-World	Random
0.1	44	44	43
0.3	63	63	60
0.5	80	79	69
0.7	87	87	76

Table 7: *n=30*

Learning effects α	Lattice	Small-World	Random
0.1	44	44	44
0.3	62	63	61
0.5	78	79	72
0.7	86	86	79

Table 8: *n=40*

Learning effects α	Lattice	Small-World	Random
0.1	44	44	43
0.3	62	62	60
0.5	79	77	73
0.7	86	85	79

WORKING PAPER

PREVIOUS ISSUES

Working Paper Publication Director : Philippe Delacote