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Technology Contagion in Networks[†]

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Abstract

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 a Moore's law (eg. solar modules) in a network of agents. We focus the analysis on the effects of the network structure and technological learning on diffusion. To this end, we study three classes of networks, namely lattice, small-world and random networks. Our numerical results show that both the lattice and the small-world networks facilitate the contagion. These networks exhibit high levels of clustering, and additional contacts increase the probability of contagion through social reinforcement. Conversely, networks exhibiting short path length and a low level of clustering (ie. random networks) guarantee an equivalent speed of diffusion with smaller ranges (ie. variance) in terms of aggregate adoption. Whatever the structure, learning effects are critical for contagion to spread in agents networks.

Keywords : Networks, Complex Contagion, Technology, Moore's law, Cascades.

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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 (ie. 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 contagions" and "complex contagions" dynamics (Centola and Macy, 2007). If the former requires only one contact for transmission (eg. information, disease), the latter calls for multiple sources of reinforcement to induce adoption (eg. 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 (ie. a short path) allows for simple contagion phenomena to spread faster, clustering (ie. 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 the adoption of a technology, understanding how network structure affects diffusion cascades is important for effective policy design.

A relevant issue to explore for network studies is the case of technology diffusion (Halleck Vega et al., 2018). Particularly, technologies subject to a Moore's law

(i.e. costs tend to drop exponentially, at different rates that depend on the technology)[1] are of great interest as they are operating in different sectors (Farmer and Lafond, 2016). For instance, this is the case for renewables (eg. solar modules, 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 networks and the associated impacts of networks' structure on diffusion remain unstudied. For the case of technologies subject to a Moore's law, these aspects are critical as for some of them public policies support the diffusion using economic instruments (eg. clean technologies, see Blazquez, 2018). Understanding how these costly technologies spread in networks could bring new insights for designing efficient and cost saving policies. From another perspective, addressing these issues is particularly relevant to achieve a faster deployment of environmental-friendly technologies. In the context of climate change, increasing this body of knowledge is of great importance too. The present paper adds up to the literature on technology diffusion in these respects.

In order to evaluate technological cascades in 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 matches the generalized version of the Moore's law we implement here (see Farmer and Lafond, 2016) and gives to our approach a large scope of applications (eg. renewables, hardware technologies). 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 are initially switched off. Then, some agents are randomly switched, i.e., seeded. Every heterogeneous agent in the

[1] Here, we refer to a generalized version of the Moore's law as exposed by Farmer and Lafond (2016).

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 proportion of neighbors that switches exceeds his first threshold and if the cost of the technology falls below his second threshold, the agent also switches (Granovetter, 1978; Schelling, 1978). This process propagates through the network. Once an agent has switched, he remains switched forever. This assumption matches clean technologies investments (eg. solar modules) for which buyers cannot easily step away.

More generally, our model assumes that agents react to stimuli both from the local and global environments (ie. 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. Therefrom, our model allows us to investigate the diffusion of a costly product in networks of heterogeneous agents. This setting is particularly relevant as recent studies shed lights on the contagious feature of renewable technologies adoption (see Baranzini et al., 2017). Overall, we implement a singular approach to technology diffusion by considering the associated spreading as an epidemic dynamics processing among agents. 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.

We apply this model to lattice, small-world and random networks as constructed by Watts and Strogatz (1998).[2] Our objective is to investigate at a macroscopic level how diffusion spreads according to network's clustering, path length and effects of learning. If the notion of path length is obvious (distance between two

[2]Remember that lattice networks exhibit high levels of clustering and average 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 (cf. Watts and Strogatz, 1998).

agents in the network), clustering refers to what extent agents tend to create tightly knit groups (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). 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.

Regarding our main results, 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 (ie. adopters). For those interested in maximising diffusion, the latter suggests a tension between maximising spreading and uncertainty in results. In random networks, although propagation reaches lower levels, it processes at an equivalent speed as in clustered networks with a lower variability in final outcomes. Whatever the underlying structure, higher learning rates lead to larger technology adoption.

With respect to previous researches, the theoretical literature on cascades and diffusion in networks is vast. Irreversibility of our cascade dynamics (ie. diffusion) sets the present paper apart as a considerable part of researches supposes that agents can switch multiple times (Blume, 1993; 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 (eg. 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 evolutionary game theory. For certain problems, such as the possibility of contagion, the models are essentially 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. Though conclusions on what facilitates diffusion are not clear-cut, the literature suggests that, under complex contagion, innovations spread further across networks with a higher degree of clustering. In principle, 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 LTM and introducing a technological 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 apprehend cascades' features and build our comparative evaluation.

We proceed as follows. Section 2 describes the linear threshold model and the dynamics of the cascade under a two thresholds setting. Section 3 shows and analyses numerical outcomes in terms of average aggregate adoption, speed of diffusion and time of convergence for classes of networks considered. Therefrom, the relevant government seeding strategy with respect to the amount of initial seeds is presented. Section 4 discusses the main findings and lays out some directions for future research.

2 Model of cascades in Networks

2.1 Preliminaries[3]

Let $G(V,E)$ be a simple (unweighted and undirected), connected graph with a set of n agents $V{:=}\{1,...,n\}$ and a set of m links E. We denote the neighbors of $i \in V$ as $N_i(G){:=}\{j|(j, i) \in E\}$ and the degree of i as $d_i := |N_i(G)|$. A first threshold for agent i 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 $f_1(\mu)$. Each agent $i \in V$ is assigned a threshold μ_i. Let's define the threshold profile of agents as $\mu := (\mu_i)_{i \in V}$. A second threshold for agent i is a random variable θ_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 $f_2(\theta)$. Each agent $i \in V$ is assigned a threshold θ_i. As mentioned, we assume that agents' thresholds are randomly and independently drawn from uniform probability distributions as the social planner has no reason to believe that some thresholds are more likely than others (Kempe et al., 2003; Lim et al., 2016). Let's define the threshold profile of agents as $\theta := (\theta_i)_{i \in V}$. A network $G_{\mu,\theta}$

[3]For this section, we base our approach on Lim et al., (2016).

is a graph endowed with the two thresholds profiles. 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 generalized Moore's law characteristics, we assume α to be a technological learning effect on the cost function. We then evaluate the effect of learning on diffusion by discretizing α over different constant rates (ie. [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 the cost of the technology decreases from 1 to 0 with respect to the number of adopters S. That is :

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

2.2 Cascade dynamics

Let us consider dynamics of a deterministic cascade on a given network $G_{\mu,\theta}$. The binary state of agent i at time t is denoted $x_i(t) = \{0, 1\}$, corresponding to "off" and "switched". Denote by $S_t(G_{\mu,\theta})$ the set of additional switches in network G at time t. At time $t = 0$, the government seeds a random set of agents with the technology. We assume this subset of agents to be $S_0 \subseteq V$, at t_0. Hence, at $t = 1$, any $i \in V \setminus S_0(G_{\mu,\theta})$ 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).

[4] We relegate extreme scenarios α={0;1} to the Appendix, Section 2.1.

Then, for a given period $t \geq 0$, node $i \in V \setminus U_{\tau=0}^{t-1} S_\tau$ 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 its threshold μ_i and if the proportion of his 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 :

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

2.3 Expected size of cascade

The expected average size of the resulting cascade in a network can be drawn from $f(\mu, \theta)$, separable in two independent and non correlated probability density functions $f_1(\mu)$, $f_2(\theta)$. For a given graph G and S_0, we can map the realization of $f(\mu, \theta)$ to a set of switches $S(G_{\mu,\theta},\, S_0)$. Hence, we can treat $S(G_{\mu,\theta},\, S_0)$ as a random variable with a probability distribution $f(\mu, \theta)$, keeping into account the cost rule. Let us compute the expected probability of any particular agent i switching in network G, given a seeded subset of agents S_0, by taking the expectation with respect to $f(\mu, \theta)$:

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

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

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

3 General results and Analysis

3.1 Preliminaries : Numerical Setting

We consider a population of N=100 agents with n=10 connections per agent. Agents are placed on three distinctive graphs created according to the Watts Strogatz algorithm (1998).[5] The graph is unchanged within a history. Each agents 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].[6] In each single history, we randomized the agents in the seed set and the associated thresholds allocation. Resulting cascades 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 - 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.

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, average cascades lengths as well as speed of adoption convergences. This macroscopic perspective brings insights on the role of clustering, path length and learning on diffusion.

In the remainder of the paper, the curves provided are averages over 1000

[5] cf. Appendix, Section 1 for description.
[6] cf. Appendix, Section 2.1 for α={0;1}.

replications and presented for each class of networks. We expose the number of aggregate final adopters, associated 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 the clarity of presentation.

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

For lattice, small-world and random networks, Fig.1.a. and Fig.1.b. exhibit the relationship between initial seed set S_0 and average aggregate diffusion under four scenarios of learning (ie. α=[0.1; 0.3; 0.5; 0.7]). Overall, aggregate diffusion is a non-monotonic function of S_0, concave where the function equals zero at extremes [0; 100] (ie. when S_0=[0; 100], the diffusion is either null or completed). A peak in resulting diffusion (ie. after seeding) is observed when S_0 lies somewhere between 24% and 50% (cf. Fig.1.b.).

Fig.1.a. Aggregate diffusion as a function of initial seed sets

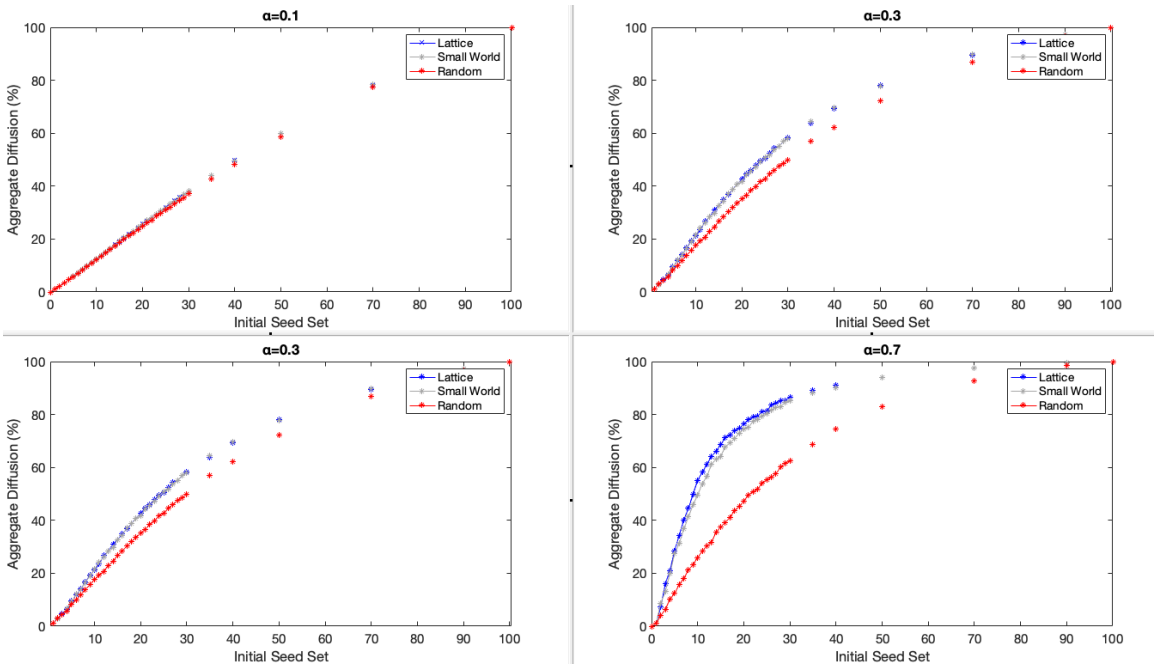
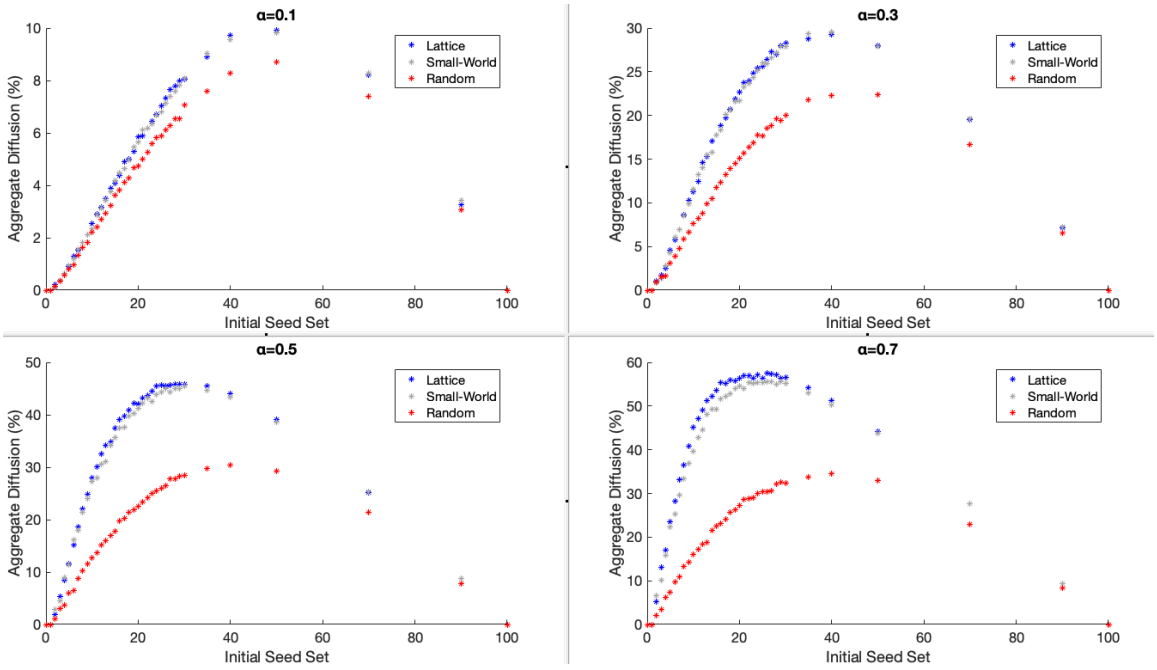


Fig.1.b. Aggregate diffusion as a function of initial seed sets (except seeds)



Precisely, for each network configuration, minimum diffusion peaks occur when α=0.1 (eg. when S_0=50, diffusion reaches 9% of adopters in random networks) while maximum peaks are observed when α=0.7 (eg. approximately 57% final adopters for 26% initial agents seeded in lattice and small-world networks). With respect to clustered structures, results suggest that the more the 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.

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 (ie. S_0=[0; 100]). Moreover, as the learning parameter grows, the diffusion gap[7] between clustered and random networks gets larger, embodying the strong influence that learning exercises 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 starts out locally, then spilling over to nearby neighborhoods, and ultimately percolating through the population of agents.

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 level of clustering, small-worlds are less clustered than lattice structures - due to some short paths crossing the whole network (cf. Appendix, Section 1). Hence, we can treat small-world as a halfway structure 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 the associated adoption gaps between considered networks.

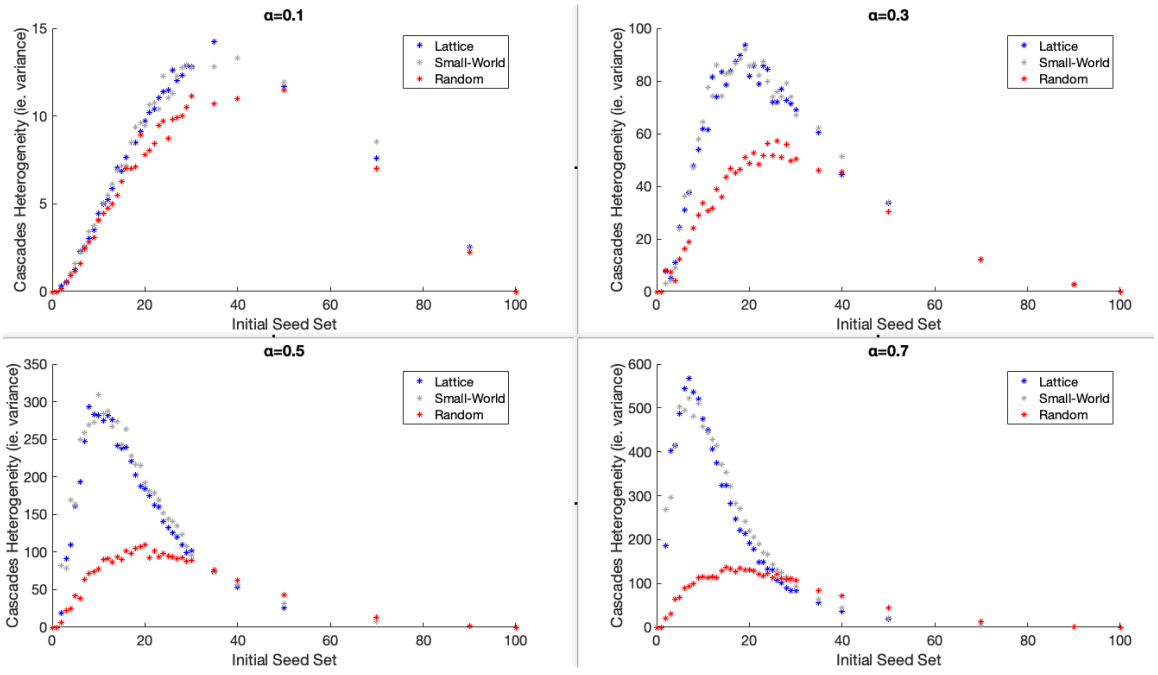
Overall, our results suggest that clustered structures and learning effects favour the adoption of a technology subject to a Moore's law. These networks exhibit higher diffusion levels compared to dynamics examined in random networks.

[7] cf. Appendix, Section 2.1.

3.3 Understanding diffusion (II) : Cascades' spreading

We are now interested in evaluating the heterogeneity of aggregate diffusion with respect to networks. We base our analysis on the variance 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. Fig.2. reports the variance of aggregate diffusion as a proxy for heterogeneity. Interestingly, heterogeneity and diffusion behave in a similar manner. In every scenario, two peak curves are obtained for clustered networks, displaying highest levels of disparity in cascades outcomes. Heterogeneity increases as a function of learning with larger ranges for clustered networks (eg. 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).

Fig.2. Diffusion heterogeneity measured by variance



To gain more qualitative insights on this issue, we map the dynamics of diffusion and heterogeneity in the case of a one threshold scenario (θ_i).[8] By doing so, we can precisely estimate the impact of adding an additional threshold (ie. cost) on diffusion features. Then it is clear that, in the absence of a cost threshold, heterogeneity decreases as a function of initial seeds in clustered networks. In our scenarios, an increase in learning brings levels of variance and diffusion closer to the ones observed in a one threshold setting (θ_i). Here, we suggest that a fast decrease in the cost function (ie. generated with high learning parameters) makes the cost condition to adopt more easily met (cf. Eq.**(1)** in Section 2). More generally, adding a second condition to adoption (ie. cost threshold) leads to a different behavior of heterogeneity in clustered networks compared to a one threshold configuration. Indeed, 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. For random networks, diffusion and heterogeneity follow the same pattern in the two designs.

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 tend to be subject to a clear "rigidity" in terms of diffusion dynamics. On 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 (ie. where the initial agents are seeded), the diffusion is caped 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 all neighborhood possible. Here, heterogeneity of our aggregate diffusion results reinforces this view

[8] cf. Appendix, Section 2.5.

- that technology only "diffuses" in random networks while in clustered networks, diffusion is exacerbated to one extreme or another (ie. low or high level). This observation suggests a possible trade-off between maximising adoption and heterogeneity. 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, the previous observation calls for a different policy approach with respect to the objective targeted.

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 question and examine how spreading dynamics is affected by the network structure. We name "time of convergence" the number of time periods required for the cascade process (ie. a simulation) to stop. For easiness of presentation, we only consider lattice and random networks as small-world configurations mimic lattice curves. In addition, we focus on scenarios where S_0=[5; 35][9] as they exhibit the main interesting outcomes.

Then, Fig.3.a. and Fig.3.b. show the relationship between the total amount of simulations (ie. 1000) in percentage and the associated speed of convergence, reported up to 32 time periods. 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.

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

Fig.3.a. Rate of Cascades convergences as a function of time, S_0*=5*

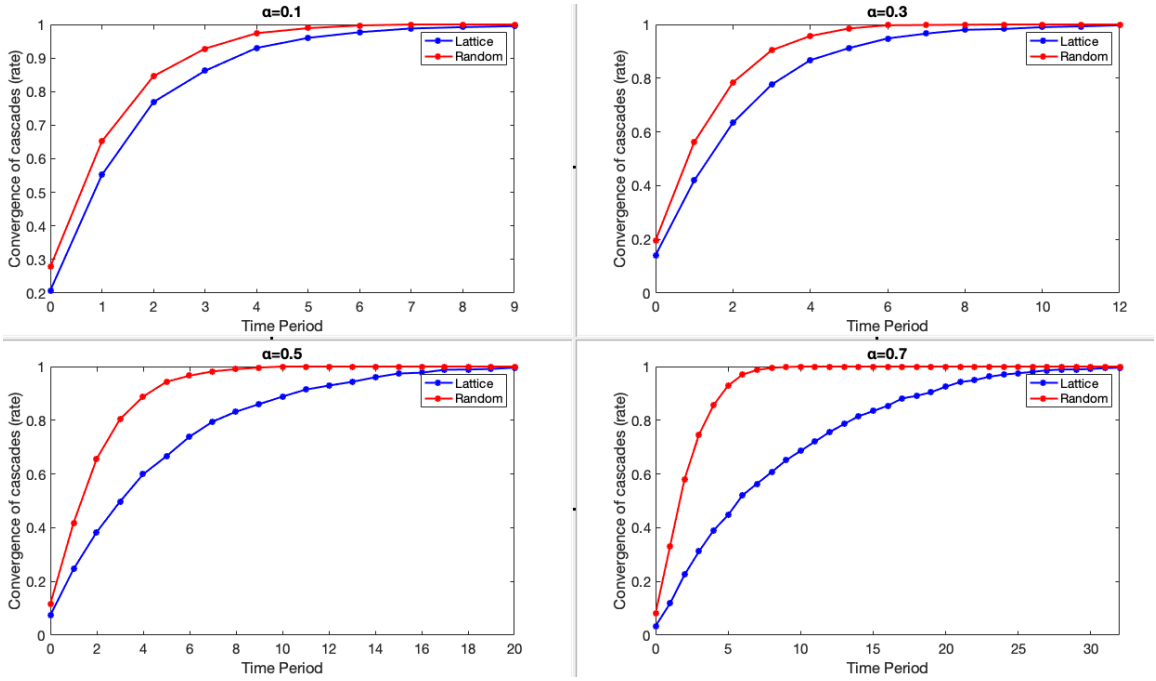
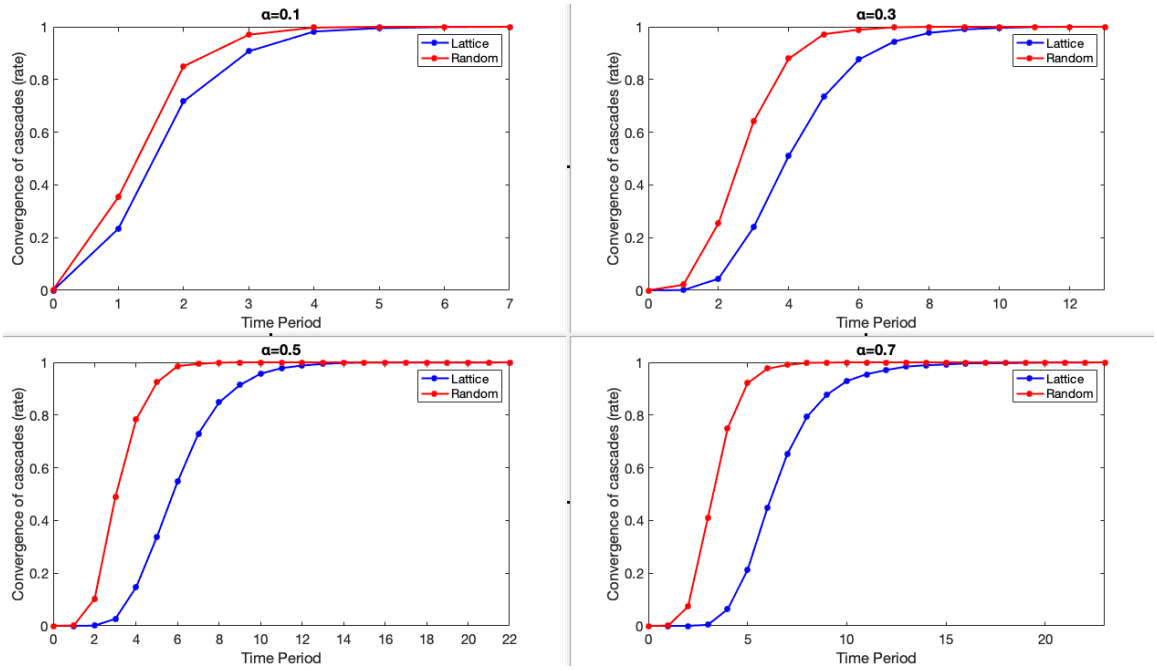


Fig.3.b. Rate of Cascades convergences as a function of time, S_0*=35*



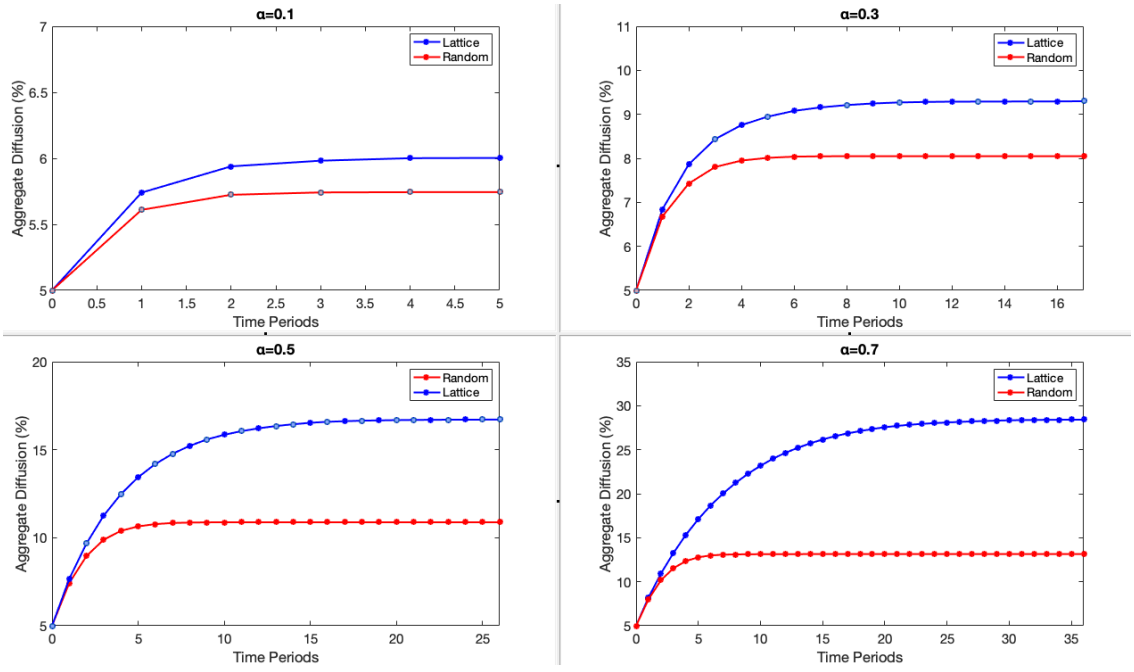
For lattice networks, early diffusion tends to spread slower than in random networks (eg. at t≤4, some scenarios exhibit rates of convergence lower than 5%, cf. α=0.7,

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 the initial seed set. 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).

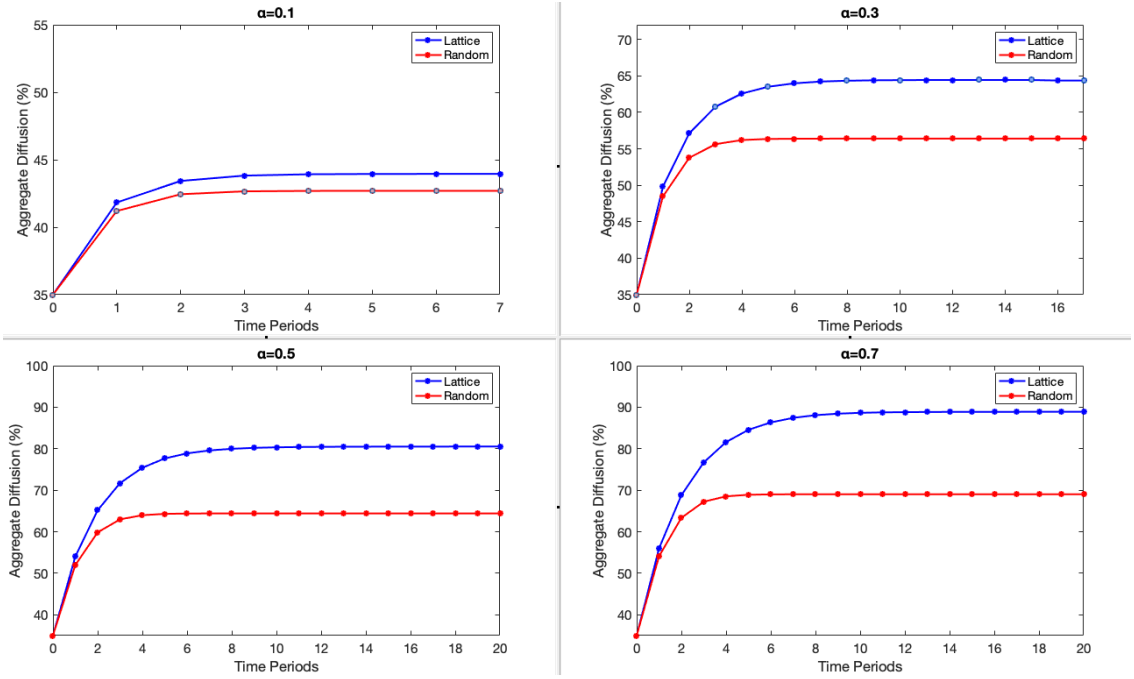
In order to strengthen our claim, we map in Fig.4.a.b. the associated times of convergence[10] with respect to aggregate amount of adopters at each period for S_0=[5; 35].

Fig.4.a. Adoption dynamics as a function of time, $\boldsymbol{S_0=5}$



[10] cf. Appendix, Section 2.4 for other scenarios.

Fig.4.b. Adoption dynamics as a function of time, S_0*=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 (ie. variance) in cascades processes 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 a Moore's law, 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.

3.5 Efficient Strategy : Tipping Points in Seeding

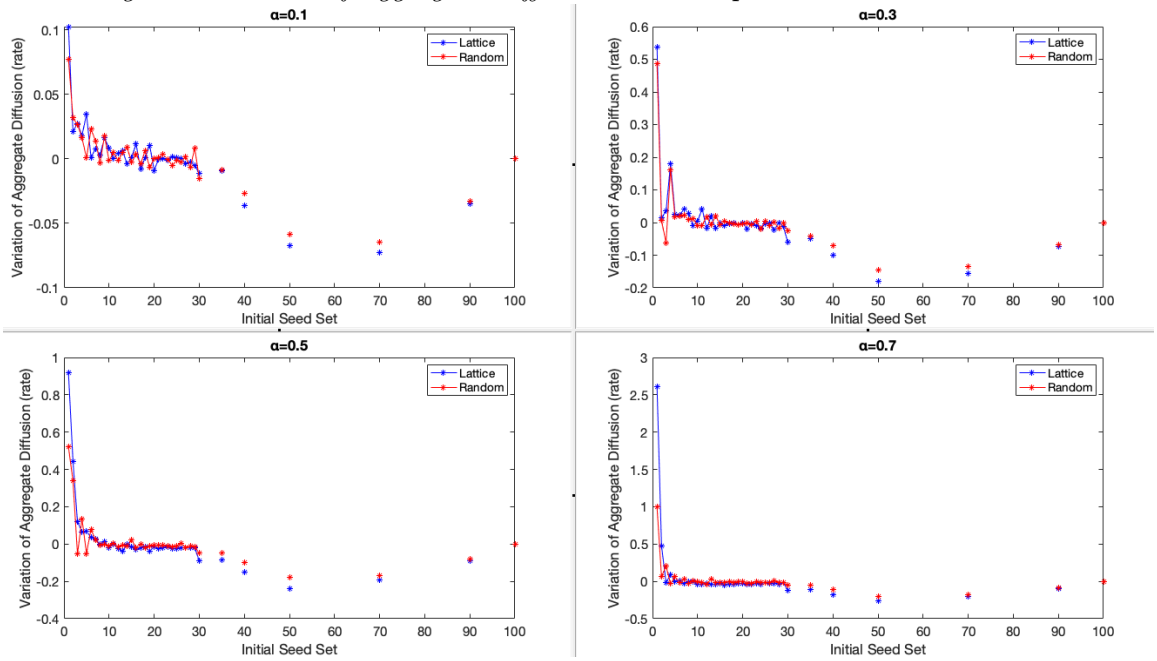
From a government perspective, maximizing or limiting the spread of diffusion comes with a cost of action (eg. number of seeds in our case). These issues have been largely documented in the literature (Kempe et al., 2003; Akbarpour et al., 2018). In the context of climate change, deploying environmental-friendly 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 (ie. 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. As previously observed, an increase in the learning parameter leads to larger diffusion and to lower associated amounts of seeds required (ie. 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 (ie. cost) on aggregate diffusion.

To address this question, we map in Fig.5. the variation of the ratio of aggregate diffusion and initial seeds in lattice and random networks (ie. high and low clustered structures). If the corresponding value is positive, seeding the associated amount of agents is beneficial for diffusion. On the contrary, a negative value suggests that the size of the seed set outweighs the final diffusion benefits (ie. adopters). From Fig.5. we note that the learning parameter has two main effects : first, moving from low to high levels of learning decreases the angular pattern of variation observed. Second, higher learning parameters lead to a smaller amount of initial seeds subject to positive ratio values.[11]

[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).

Overall, the level of initial seeds having positive values is always lower in clustered networks compared to random networks which makes a government intervention (ie. 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.

Fig.5. Variation of aggregate diffusion with respect to initial seed sets



4 Discussion and Conclusions

For some types of technologies, the cost of a unit decreases exponentially over time (Moore's law). As for hardware technologies, green technologies like solar modules follow this trend (Farmer 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 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 (eg. subsidies). In this paper, we provide clear evidences that under a complex contagion process, clustered organizations are crit-

ical 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 for policy makers. Among those, targeting clustered organisations (eg. 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 level, they also generate a high heterogeneity in aggregate adoption. 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 (eg. case of renewables).

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 an 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 thresholds 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. 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 (eg. hardware, chemical and energy - technologies subject to a Moore's law).

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Appendix

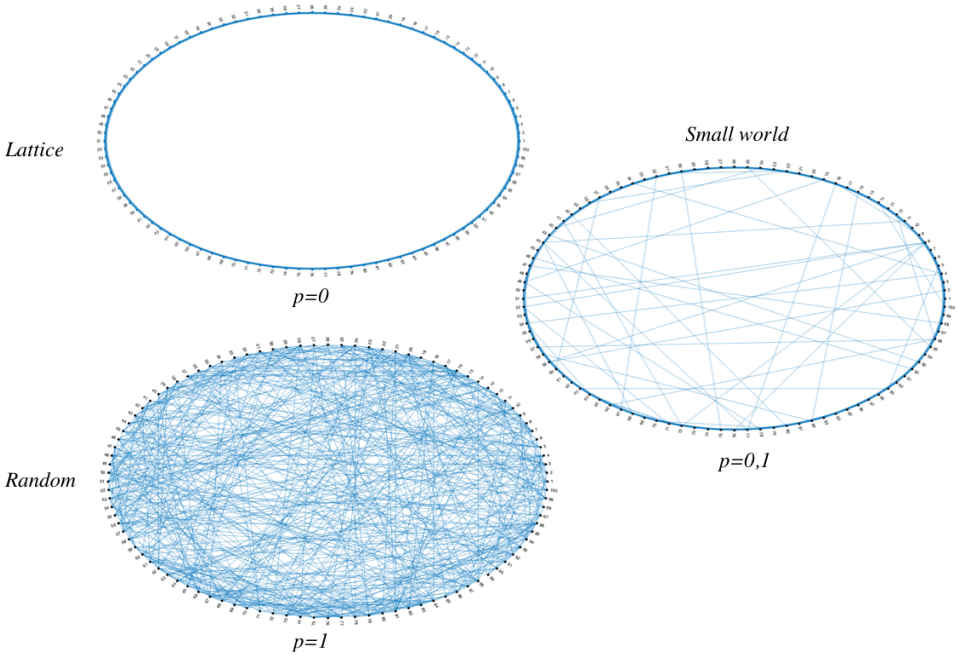
1. Watts Strogatz algorithm

In this section, we based our approach on Cowan and Jonard (2004). Let $I = \{1,...,N\}$ denote a finite set of 100 agents. For any $i, j \in I$, we set the binary variable $\chi(i, j)$ to take the value $\chi(i, j)=1$ if a connection exists between i and j, and $\chi(i, j)=0$, otherwise. The network $G = \{\chi(i, j); i, j \in I\}$ is the list of all pairwise relationships between agents. The neighborhood of i is the set $\Gamma i = \{j \in I : \chi(i, j)=1\}$. A path in G connecting i and j is a set of pairwise relationships $\{(i, i_1),...,(i_k, j)\}$ such that

$\chi(i, i_1) = \cdots = \chi(i_k, j)$=1. Finally, the distance $d(i, j)$ between i and j is defined be the length of the shortest path between them. The following algorithm (Watts and Strogatz, 1998) allows us to construct a family of constant networks density graphs which lie between a nearest-neighbor graph on a periodic lattice (also named regular graph), and at the other extreme a random graph with uniform degree.

Create the regular periodic lattice with n nearest neighbors (n even). Sequentially, consider each edge of the graph; with probability p disconnect one of its vertices, and connect it to a vertex chosen uniformly at random. Check both that vertices do not get self-connected (loop), and that no two nodes are connected more than once. For large graphs, this procedure ensures that G is connected. By setting p, we vary the graph structure from completely regular (p=0), through intermediate states, (0<p<1), to completely disordered (p=1). This creates variation in the number of edges per agent, but maintains an average of n connections per agent and a total of $Nn/2$ edges, $\forall p$. Define $G(n;p)$ to be the graph produced by this algorithm. Fig. 1 depicts three illustrative configurations with increasing disorder as p is increased, for N=100 and n=10.

Fig.1. The transition from a locally ordered network to a disordered one via small world.



Watts and Strogatz (1998) point out that the structural properties of *G(n;p)*-graphs are intuitively captured by the concepts of average path length and average clustering. Define the clustering of a set $S \subseteq I$ to be 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, it is the share of friends of on individual who are also friends of each other. Clustering or cliquishness can be used to measure local coherence or redundancy by taking S to be the neighborhood of an agent. Then the local coherence in the network is measured by the average neighborhood cliquishness $C(p) = \sum_{i \in I} cl(\Gamma_i)/N$. Average path length is $L(p) = \sum_{i,j \in I} d(i,j)/(N(N-1)/2)$, the average number of steps separating two randomly chosen agents. Though a natural conjecture is that cliquishness and path length are strongly correlated, there is a non-negligible interval for p over which $L(p) \simeq L(1)$ yet $C(p) \gg C(1)$. This interval constitutes the small-world region. It arises because when the number of long distance links is small, their marginal effect on average path length is large: introducing a long-range edge provides a shortcut not only between the two nodes that this link connects, but also for their immediate neighbors, the neighbors of those neighbors and so on. By contrast removing one local link affects the cliquishness of only a small number of neighborhoods and therefore has little effect on the population average. The evolution of path length and clique size with p is shown in Fig. 2, extracted from Cowan and Jonard (2004), for a graph of N=100 nodes, each vertex having on average n=10 nearest neighbors. For the sake of clarity, we plot the averaged normalized values $L(p)$=$L(0)$ and $C(p)$=$C(0)$ over a sample of 500 different graphs. Normalized average cliquishness remains almost constant when p is reasonably small and falls slowly for large values of p. By contrast, average path

length falls quickly for very small p values and then attens out. Hence, for $p \in$ [0.01,0.1], cliquishness and path length diverge, creating a small world region in the space of network structures.

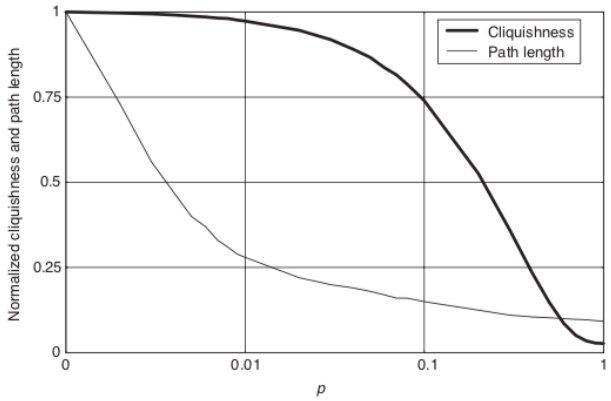


Fig. 2. Average cliquishness and average path length as function of p.

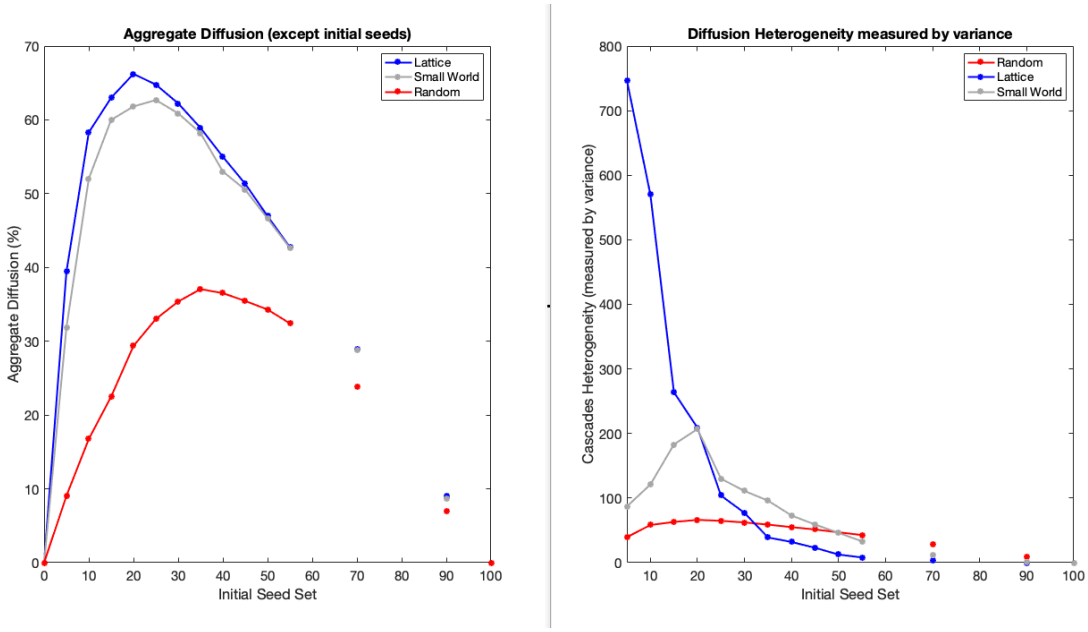
2.1 Aggregate diffusion and variance, α=[0;1]

1) For α=0, the cost function is :

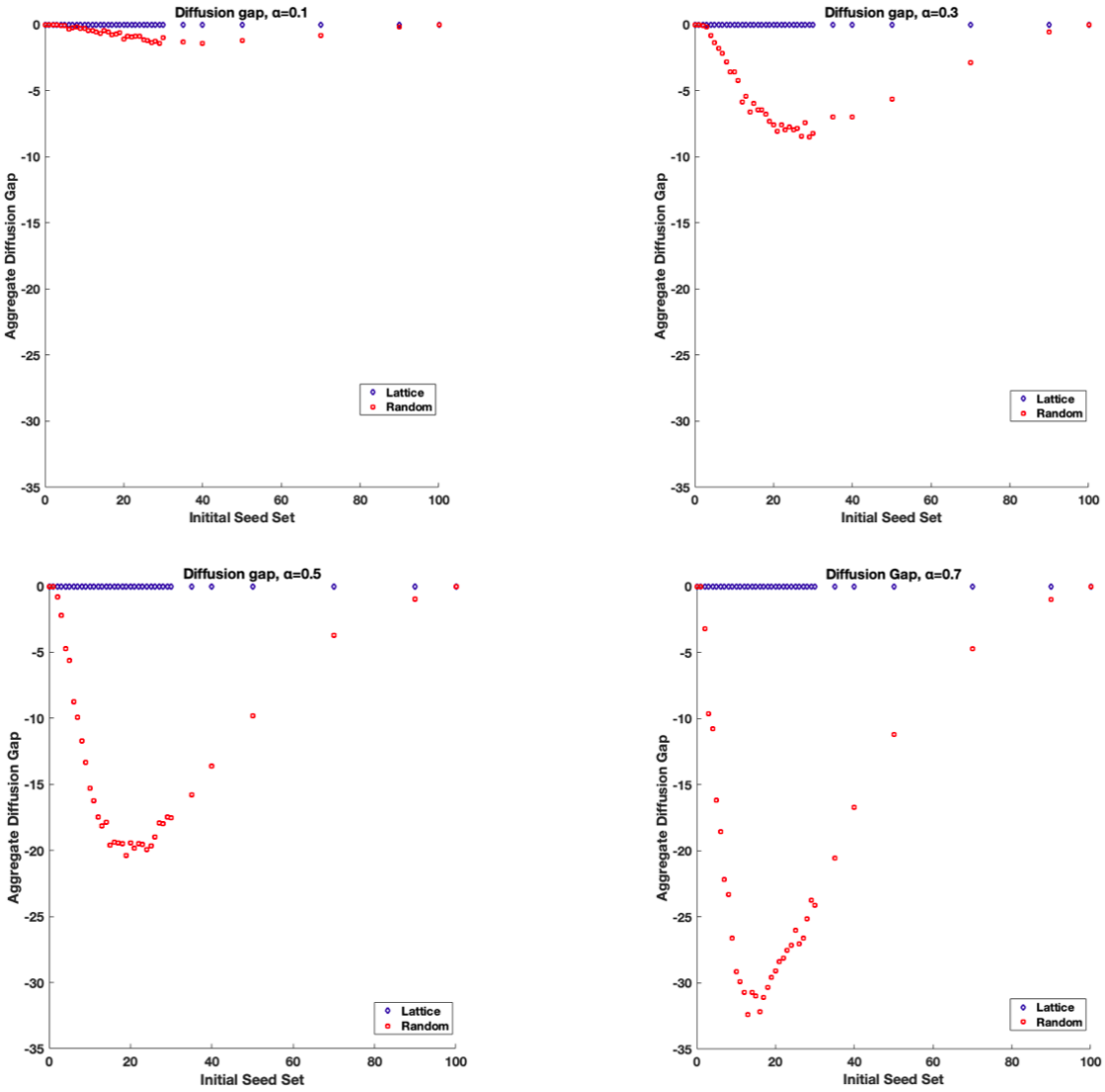
$$C_t = C_0 \times (|U_{\tau=0}^{t-1} S_\tau|)^{-0} = 1$$

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):

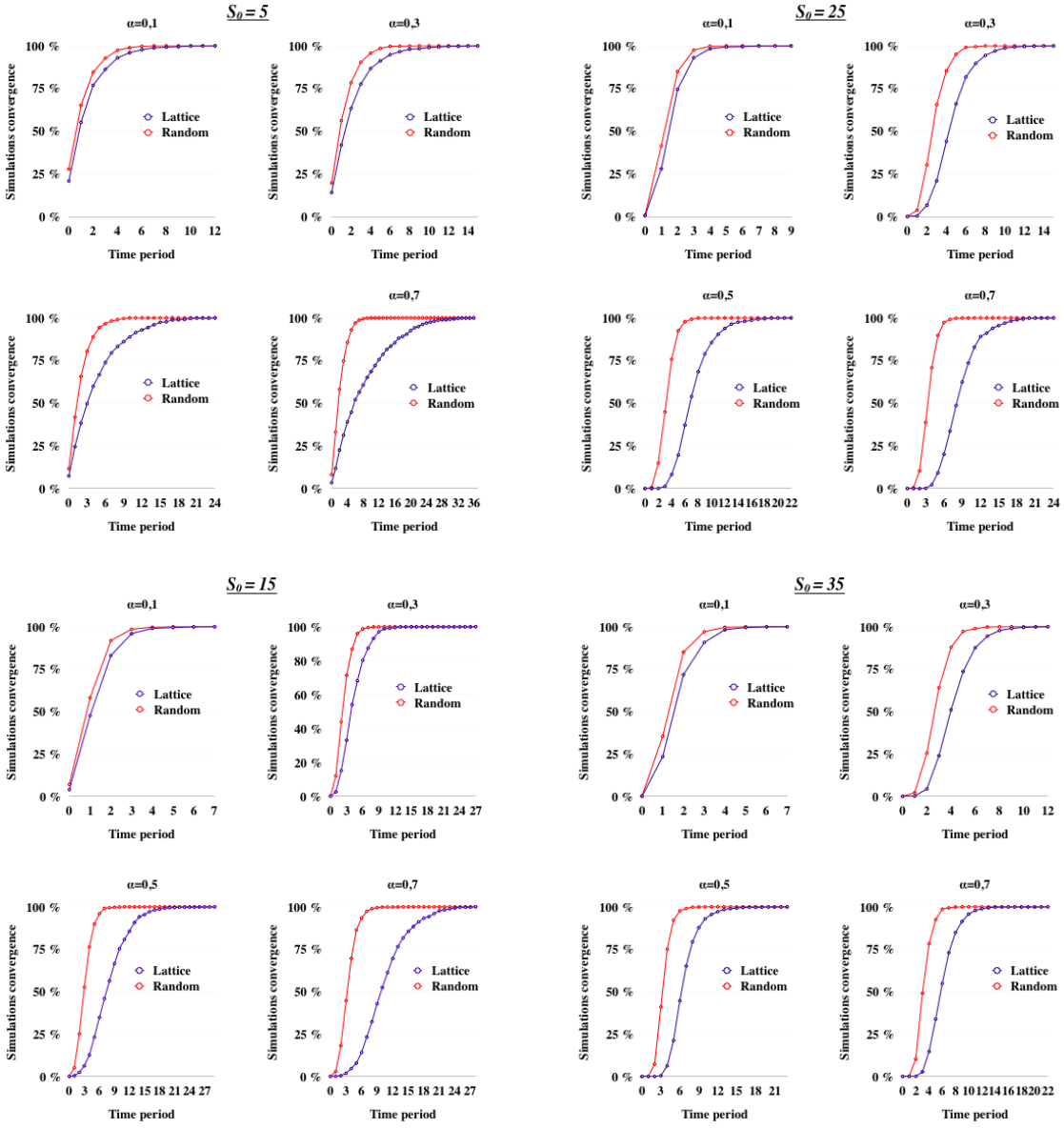


2.2 Diffusion gaps



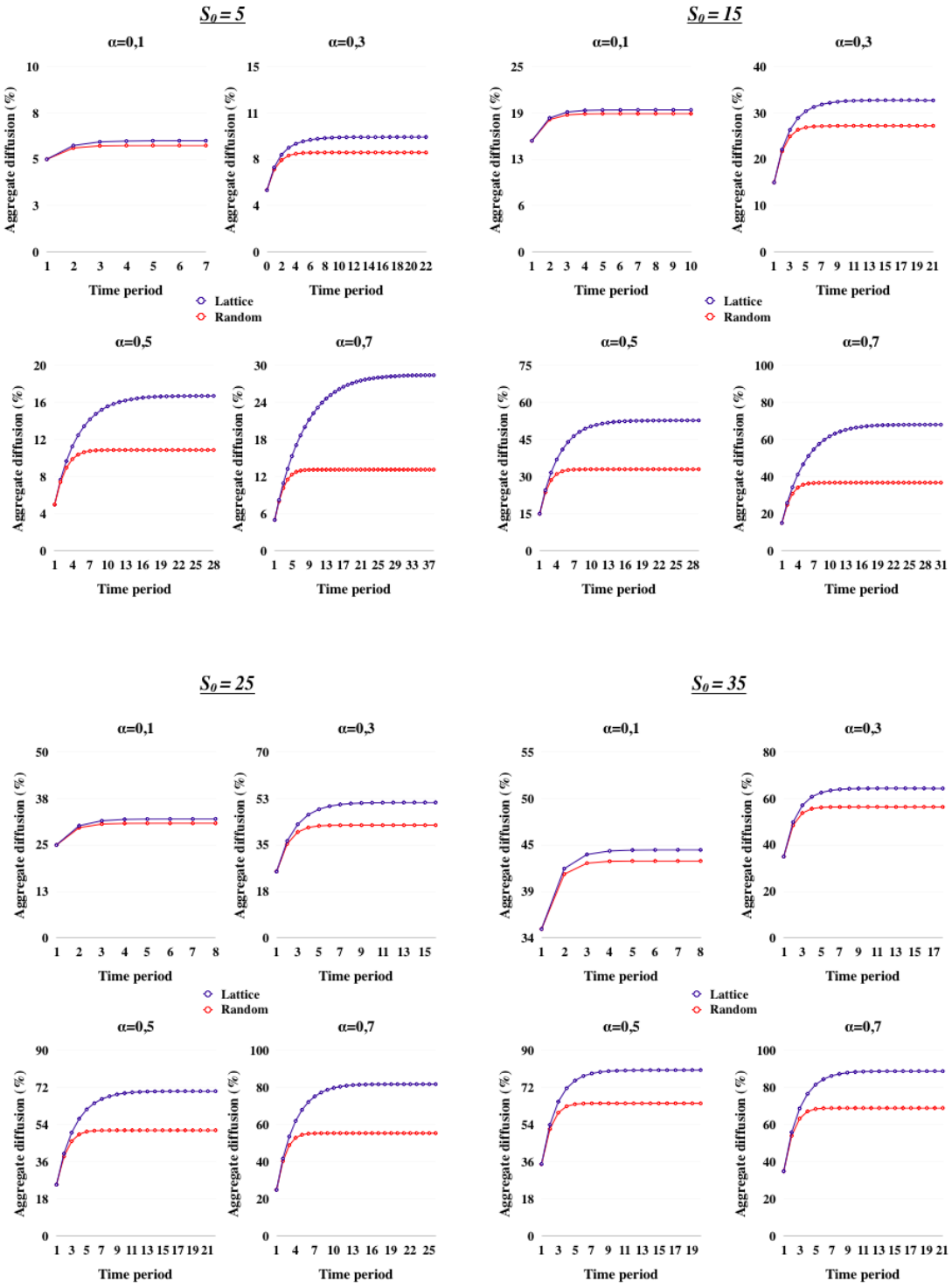
Diffusion gaps, baseline lattice

2.3 Cascades convergences



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

2.4 Adoption convergence



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

2.5 One threshold scenario θ_i

Aggregate diffusion (except initial seeds) and heterogeneity in a one threshold scenario