The Effect of Negative Word-of-Mouth on Innovation Diffusion and the Performance of Marketing Strategies: an Agent Based Percolation Model

A master thesis by

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Abstract

Because real-world marketing experiments are costly, firms make use of diffusion models to decrease uncertainty. Over the last few years Agent Based Models of Percolation have received increased attention in the literature, in which awareness of an innovation diffuses through social contagion, and price and promotion (seeding) strategies can be experimented with (cf. Solomon et al., 2000).

A limitation of the basic percolation model such as Solomon et al. (2000) is that consumers in a social network only receive information about the existence of an innovation, but their own attitude towards the adoption of the innovation remains unaffected by that of their neighbors under the influence of Positive- and Negative Word-of-Mouth (PWOM and NWOM). Although the effects of PWOM and NWOM have been studied empirically, only few extensions on the basic percolation model have been made capturing this effect (e.g. the NWOM model by Erez et al. (2004), and the social reinforcement model by Mas Tur (2016)). This research addresses a gap in the literature studying the effect of NWOM on percolation size and exploring the performance of price and promotion (seeding) strategies given there is NWOM. The standard percolation model is extended with the effect of NWOM in the decision process of an actor, coming from rejecting neighboring actors.

It is found that, given there is NWOM, percolation size decreases and the steepness of the percolation threshold increases. This implies that percolation size, and therefore revenue, decreases and becomes more sensitive to price changes. Although the relation between network structure and social influence is studied by e.g. Mas Tur (2016), we have explored this relationship in depth and have identified new mechanisms which causes the relative decrease in percolation size, given there is NWOM, to be higher on clustered networks as opposed to random networks.

Regarding seeding strategies, it is found that increasing the number of seeds increases percolation size and that the relative decrease in percolation size given there is NWOM is lower for a high number of seeds as opposed to a low number of seeds. Furthermore, since promotion strategies can be targeted towards specific customers we have studied how percolation size differs by picking seeds with different network centralities. We have found that seeds which are placed far apart from each other and have a high degree centrality are particularly effective when aiming for high percolation size and that the relative decrease in percolation size given there is NWOM is lowest for seeds that have short path lengths to other agents in the network (betweenness and closeness centrality).

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1. Introduction

The success of innovations is highly uncertain and successful market penetration is largely dependent on whether the chosen price and promotion strategies are in line with the market (Kotler & Armstrong, 2010). Because testing different strategies in a market is expensive and sometimes even impossible (Borschev & Filippov, 2004), strategies are experimented with in virtual worlds to decrease this uncertainty (Sterman, 2000). An innovation diffusion model is such a virtual world, and it may provide insight in market behavior.

According to Rogers (2003) innovation diffusion is defined as: (1) an innovation (2) that is communicated through certain channels (3) over time (4) among the members of a social system. First hypothesized by Lazarsfeld et al. (1944) and later used in the two-step flow model by Katz (1957), an innovation can be communicated through two channels: an external source, such as promotional activities or mass media, and an internal source, referring to social contagion or imitation. The latter is captured by the concept of Word-of-Mouth (WOM), which can be defined as the information about the innovation that is communicated among consumers. The insights of the two-step flow model led to the development of one of the most influential diffusion models of the 20^{th} century, the Bass-model (Bass, 1969). The Bass-model is a mathematical formula, explaining the s-shaped product life cycle of introduction, growth, maturity and decline (Kotler & Armstrong, 2010). However, relying on estimated parameters the Bass-model is particularly useful for *understanding* historical behavior rather than *forecasting* behavior (Kiesling et al., 2012). Furthermore, using a single formula, consumers are completely homogeneous. Due to this high level of abstraction the model lacks explanatory power on *"innovation failures, oscillations and collapses of initially successful diffusions*" (Kiesling et al., 2012, p108). Because the model does not take into account that some consumers are linked whilst others are not (the structure of the social network), and these consumers have different preferences (Kiesling et al., 2012), with the increase of (cheap) computing power the Agent Based Modelling (ABM) approach has become popular which is a methodology that overcomes these limitations. For the subject of innovation diffusion, ABM is particularly useful because the market *"[...] contains active objects (people, business units, animals, vehicles, or projects, stocks, products, etc.) with timing, event ordering or other kind of individual behavior."* (Borschev & Filippov, 2004, p19).

A phenomenon which has gained particular interest over the last few years in Agent Based Modelling of diffusion is social percolation (Solomon et al., 2000; Goldenberg et al., 2000; Erez et al., 2004; Delre et al., 2010; Campbell, 2013; Zeppini & Frenken, 2015; Mas Tur, 2016). Social percolation is an application of percolation theory, which is widely applied in (for example) physics and chemistry to study the diffusion of a gas or fluid in a porous material[1]. Social-percolation assumes that consumers form a "porous" social network through which information diffuses from one agent to another. When subjected to innovation diffusion, the information communicated is simply the information that an innovation exists. Once informed, the agent get to decide whether to adopt or reject the innovation. In basic Agent Based Models of Percolation (ABMP) agents either adopt or reject by comparing their individual preferences with a characteristic of the information, such as quality (Solomon et al., 2000; Goldenberg et al., 2000; Erez et al., 2004; Delre et al. 2010; Mas Tur, 2016) or price (Campbell, 2013; Zeppini & Frenken, 2015). When the quality is increased, or the price is lowered, the information will meet the preferences

[1] An example of percolation is hot water percolating through grinded coffee. The aim of percolation is here for water to percolate from the top of the coffee to the cup underneath.

of a larger number of consumers. The higher the number of adopters the higher the so called 'percolation size', which is expressed as the fraction of adopters of the entire number of agents in the network.

Although being a rather complex process in the real world, for modelling purposes it is usually assumed that information is only spread by those who adopt the innovation while those who have been informed but decide not to adopt are assumed not to spread the information. In this respect, WOM can be understood as the literal communication process of one adopter telling about an innovation to a potential adopter, but also as information spreading through observation, that is, a potential adopter observing an innovation being used by another adopter (e.g., on the street, through visits, etc.). For convenience, we will refer to both cases as WOM.

What percolation theory has contributed to the diffusion literature is the insight that the process of social contagion may be limited because of the structure of the network. That is, as information of the existence of an innovation only spreads through WOM – and only adopters spread this information while non-adopters do not – it may well be the case that this information never reaches all parts of the social network with potential adopters. Because of these network inefficiencies the relationship between price or quality and percolation size is highly non-linear (Solomon et al., 2000). However, at a critical value for price or quality, the *percolation threshold*, this limitation can be overcome. That is, there exist a critical quality or price below which diffusion is almost absent and above which diffusion is almost full. Therefore, a small deviation from the threshold might result in unsuccessful market penetration.

A limitation the basic models of ABMP holds is that it assumes that consumers in a social network only receive information about the existence of an innovation, but their own attitude towards the adoption of the innovation remains unaffected by the adoption decision of their neighbors. We refer to this as *simple propagation* as the information communicated is only *neutral* WOM. However, in the psychology and marketing literatures it is widely recognized that the process of WOM often also affects the attitudes (or preferences in economists' language) of individuals (Oliver, 1980). Such an adjustment of attitudes is also referred to as *complex propagation*. In the case in which consumers recommend an innovation, we speak of Positive Word-of-Mouth (PWOM) and potential consumers become more likely to adopt, and diffusion will be enhanced. By contrast, consumers may also discourage others to adopt an innovation, to which one refers to as Negative Word-of-Mouth (NWOM) which may hamper further diffusion. In particular, *"[…] disappointed consumers tend to spread more NWOM and have higher effect on other consumers"* (Erez et al., 2004, p. 9). Because of the dangerous effects of NWOM, firms engage actively in monitoring NWOM and intervening with apologies, compensations and corrective actions (Lee & Song, 2010; Van Noort & Willemsen, 2011).

The effects of PWOM and NWOM have been studied widely, and empirical evidence indicates that it affects, for example, the revenue in the movie industry (Liu, 2006; Duan et al. 2008), hotel room sales (Ye et al., 2009) and book sales (Chevalier & Mayzlin, 2006; Amblee & Bui, 2011). NWOM and PWOM, however, have received little attention in ABMP. Exceptions are the model on NWOM (Erez et al., 2004), and the models by Delre et al. (2010) and Mas Tur (2016) on PWOM. Since the effect of NWOM is of high importance to firms, while very few models exist compared to PWOM, the aim here is to develop a model of NWOM. Since the research by Erez et al. (2004) on NWOM leaves the subject of percolation size untouched, the following research question is addressed:

Research Question 1: To what extent does Negative Word-of-Mouth affect the diffusion size of an innovation?

In particular, we are interested in how the effect of NWOM on percolation size differs for different network structures. The exploration of small world networks is particularly useful for the practical relevance of this research as these networks have proven to have properties of real life social and physical networks (Watts & Strogatz, 1998; Zeppini & Frenken, 2015).

Sub-Question 1: To what extent does the structure of networks affect NWOM?

Answering these two questions allows to better understand the relation between innovation price and percolation size given there is NWOM, and allows to explore different price related marketing strategies. However, adjusting the price is not the only marketing tool available. An alternative strategy is the targeting of consumers by free offerings, also known as *seeding*. The number of offerings and the socio-economic status of the targeted consumers might affect the percolation size as well. In network theory the socio-economic status of an agent can be related to its centrality in the network. Examples of centrality are the number of neighbors (degree centrality) or having neighbors with a lot of neighbors (eigenvector centrality). In this research we will explore two different seeding strategies and how they perform given there is NWOM.

Research Question 2: To what extent does adding seeds change the percolation size given there is NWOM?

Research Question 3: To what extent does picking agents with high centrality as seeds change the percolation size given there is NWOM?

The contributions of this research are threefold. Firstly, this research will address a gap in the diffusion literature by analyzing the effect of NWOM on percolation size, i.e. the extent to which an innovation with a certain price diffuses in a market. Secondly, the model will be of particular interest to managers and policy makers, as it will allow for an exploration of alternative price and promotion strategies depending on whether there exists NWOM. These questions have not yet been addressed in the context of ABMP and NWOM. Thirdly, the model will contribute to the research by TNO on market transitions. As such, it will serve as a module in a larger diffusion model focusing on competing technologies under increasing returns.

This research is organized as follows: first it will review the current state of the literature on innovation diffusion, consumer behavior, Positive- and Negative Word-of-Mouth, and Agent Based Models of Percolation; next, a suitable methodology for the research shall be presented; followed with the results from the experiments. The results will be interpreted in the conclusions and finally the implications and the contributions of the conclusions will be discussed.

2. Literature review

The literature review will start with the introduction of the innovation adoption process (section 2.1.), followed with literature on diffusion (section 2.2.) and a discussion of different seeding strategies in section 2.3. In section 2.4. the effect of PWOM and NWOM on decision-making is discussed. Finally, in section 2.5. and 2.6. the application and implications of percolation models are reviewed.

2.1. The innovation adoption process

Researchers from different fields of science, such as innovation sciences (Rogers, 2003) and marketing (Peter & Olson, 2005; Kotler & Armstrong, 2010) agree upon the fact that the adoption decision is just a single stage in a larger process of innovation adoption and the generic model of the innovation decision process is therefore used in different research areas. The five different phases in the generic model have different names across research disciplines. In this research an interpretation of the phases by Rogers (2003) is applied (see Figure 1): 1) the consumer becomes aware of the innovation; 2) the consumer forms an attitude towards the innovation; 3) the consumer decides whether to adopt or reject an innovation; 4) the consumer implements the decision; and 5) the consumer seeks confirmation with its neighbors on its decision. During this confirmation phase the agent reconsiders its previous decision. Initial adoption may lead to continued adoption or discontinuance, whilst initial rejection may lead to later adoption or continued rejection.

Although the linear nature of this generic model is criticized, Peter & Olson (2005) argue that the model *"[…] is flexible enough to account for the nonlinear, continuous flow of interactions amongst behaviors, environments, and cognitions, and for the multiple decisions that occur in actual consumer problem-solving episodes"* (p.169). Furthermore, in the ABMP being developed, the focus is not on the individual decision-maker as such, but on the way and extent social networks affect individual decisions through NWOM as the diffusion process unfolds. Hence, the specification of individual decision-making can, in itself, remain stylized in the line of Rogers' model.

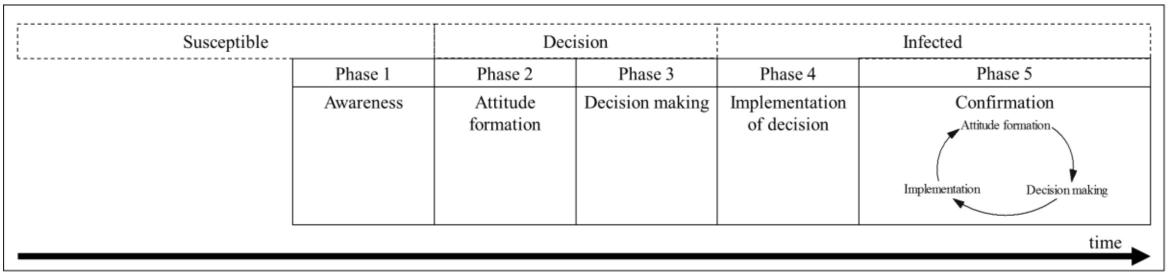


Figure 1 Interpretation of the generic model[2]

Parallels between the phases of the generic model and the Susceptible-Infected model of diffusion can be drawn as the phases can be reduced to three states an agent can be in: 1) susceptible, the state in which the consumer is not yet aware of the existence of the innovation, which ends with the infection with awareness from a neighbor through neutral WOM, 2) decision, the state in which the consumer forms an attitude and decides to either adopt or reject the innovation, ending when the consumer has made a decision, and 3) infected, the state in which the consumer adopts or rejects the innovation and becomes either infected with adoption or infected with rejection. In the next section the Susceptible-Infected model and its implications for diffusion will be discussed.

[2] Following Rogers (2003)

2.2. Diffusion of awareness

One of the most basic and most intuitive Agent Based Models of diffusion is the forest fire model (Bak et al., 1990), in which fire diffuses through a forest. The fire keeps spreading as burning trees set fire to not-burning neighboring trees, until the burning trees only have burning neighbors, or no neighboring trees at all. This model is also known as the Susceptible Infected model: a burning tree is a tree infected with fire (I) and infects its neighboring susceptible (S) trees with fire as well.

Rather than modelling the spread of a fire, in innovation diffusion the spread of information about the existence of the innovation (awareness) is modeled. The dynamics of such an information spread are dependent on three factors: 1) the structure of the system in which the infection spreads; 2) the initial number of infected agents; and 3) the mechanism of propagation (Vermeer, 2015).

2.2.1. Structure of the network

Network theory assumes that information can only be transferred from one agent to the other when two agents (nodes) have some sort of relationship. Such a relationship, the ability to interact, is also known as a link (edge). Therefore, if an agent spreads information this can only reach agents which are directly or indirectly linked to the source. Since the blue agent in Figure 2 (left) is connected in neither way to the red dotted agent the blue agent will not be able to receive the information sent from the source due to *the limitation of the network structure*. A second limitation of information diffusion is observed when *heterogeneity in attitudes* is introduced which assumes that agents can either have a positive or a negative attitude towards the adoption of information. In Figure 2 (left) all agents had a positive attitude, which implies that as soon as an agent is informed, it will adopt the information and spread it to neighboring agents. However, having a negative attitude towards the information implies that the agent will not adopt the information and will not spread the information towards neighboring agents. In Figure 2 (center) agents with a negative attitude towards the information sent by the red agent are colored blue. If we remove these agents from the network, and cancel their links, we observe *the components of the operational network* (Figure 2 right). The white agents have a positive attitude towards the information, but some of them will not be informed since they were surrounded by agents with a negative attitude.

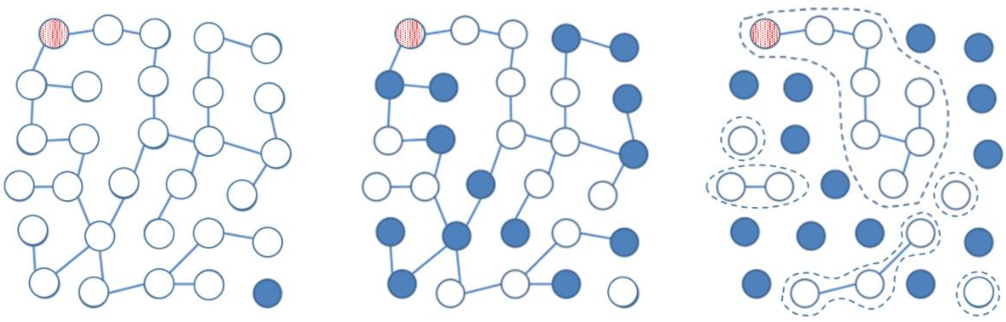


Figure 2 Network inefficiencies, attitudes and the operational network[3]

<u>Left:</u> Due to the structure of the network the blue agent is not able to receive the information sent by the red dotted agent. <u>Center:</u> Heterogeneity in attitudes: the white agents have a positive attitude towards the adoption of information whilst the blue colored agents have a negative attitude. <u>Right:</u> The white agents having a positive attitude towards the adoption of information are part of the operational network. However, due to either the limitation of the network structure or due to the negative attitude of other agents not all agents will receive the information sent by the red dotted agent. The groups (or individuals) of agents in the operational network are known as components of the operational network.

[3] Following Zeppini & Frenken (2015), page 3

In real world situations agents in small networks can be connected to everyone else in the network, such as employees in a small company. Such a network structure is referred to as a complete graph (Easley & Kleinberg, 2010) or a fully connected network (Zeppini & Frenken, 2015). However, when larger networks are considered, there might be less connectivity. Take for example a large firm: employees in a department might be fully connected, but between the departments only the managers might be connected. The departments, the parts of the network which are highly interconnected, are referred to as clusters in the network (Easley & Kleinberg, 2010).

Scientists have defined different typologies to describe and study real world networks, such as random network (Erdős & Rényi, 1959), scale free networks (Barabási, & Albert, 1999) and small-world networks (Watts & Strogatz, 1998). For the purpose of this research small-world networks are of particular interest since they have properties of real world networks: *"these systems can be highly clustered, like regular lattices, yet have small characteristic path lengths, like random graphs. We call them 'small-world' networks, by analogy with the small-world phenomenon"* (Watts & Strogatz, 1998, p440)[5]. A small-world network start with N agents in a one dimensional regular ring lattice with all agents having the same number of links (also known as the degree of an agent). The small world phenomenon emerges when links are rewired with the probability μ (also referred to as the rewiring probability), reducing the average path length as the rewired links make shortcuts between parts of the network whilst keeping the clustering of the network somewhat equal (see Figure 3). Therefore, a network with μ=0.000 (no rewiring) remains the regular lattice (Figure 4 left), the network with μ=0.100 (Figure 4 center) represents a network with small world properties, whilst a network with μ=1.000 (Figure 4 right) is referred to as a random network, a Poisson network or an Erdos-Renyi model (Erdos and Renyi, 1959).

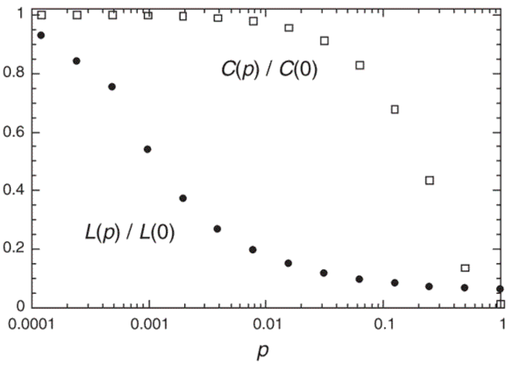
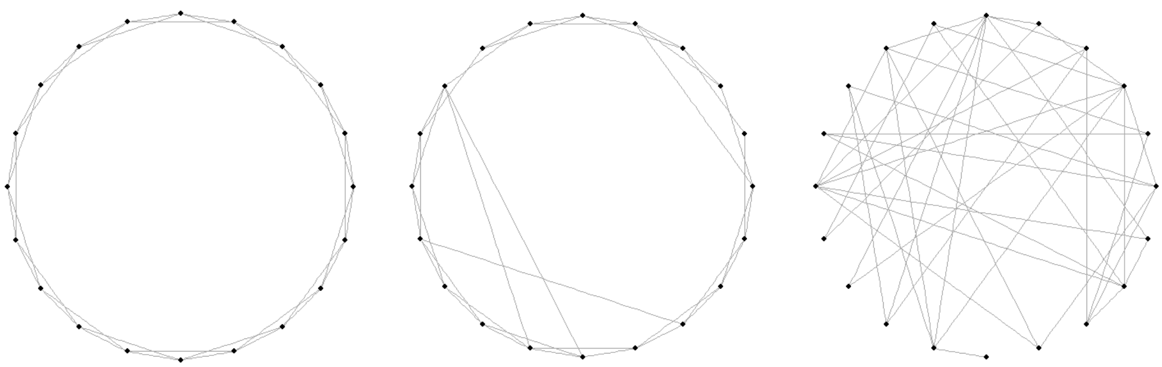


Figure 3 Clustering (C) and path length (L) in small world networks[4]



μ=0 *μ=0.1* *μ=1*

Figure 4 Rewiring of links[6]

[4] From Watts & Strogatz (1998) page 441. Rewiring probability p referred to as μ in this research
[5] The small world phenomenon is popularly known as the 'six degrees of separation'. This assumes that any person is only six handshakes separated from any other person on this planet (Easley & Kleinberg, 2010)
[6] With N=20 agents and an average degree of 4

Zeppini & Frenken (2015) have studied the relationship between the network structure, small-world networks in particular, and percolation. They have found that with increasing randomness, or with an increasing number of rewired links, the size of the components in the operational network increases leading to higher percolation size. Furthermore, Mas Tur (2016) has studied the impact of the network structure on complex propagations and has found that social reinforcement (PWOM) has a higher impact on percolation size for clustered networks as opposed to random networks since clustering links *"[…] provide additional support for the social reinforcement decision"* (Mas Tur, 2016., p81).

2.2.2 The number of seeds

As Bass (1969) pointed out, for imitation to occur one or more initial adopters are required, known as the seeds of infection. These initial adopters may occur at random, as a result of free offerings or promotion efforts leading to innovation by innovative consumers, or may be carefully planned as a result of direct marketing (Kotler & Armstrong, 2010). Seeds are used to activate the components of the operational network. A single seed, if placed in the operational network, can only activate one component of the operational network (Figure 5 left). Increasing the number of seeds may prove to be effective as it might activate multiple components of the operational network (Figure 5 right). Furthermore, increasing the number of seeds may prove to be effective as it increases the probability that at least one seed will be placed inside a component of the operational network. A seed is placed outside a component of the operational network when all its neighbors are rejecters, which is also referred to as *unlucky seeding*.

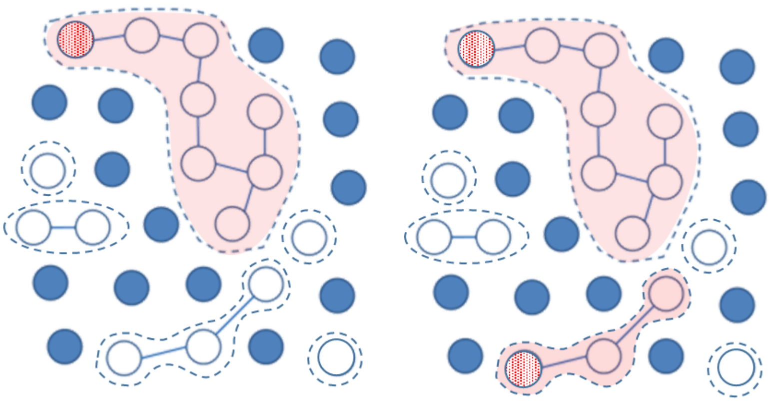


Figure 5 Activation of components in the operational network[7]

Left: a single seed activating one component of the operational network. Right: two seeds activating two components

[7] Following Zeppini & Frenken (2015), page 3

2.2.3. Mechanism of propagation

The probability of successful propagation, a process in which *"[…] the (change in) state or behavior of one actor results in a change in state or behavior of one or more of its connected neighbors"* (Vermeer, 2015, p.15), is dependent on the characteristics of the infection. Although the fire in the earlier mentioned forest fire model always propagates from an infected to a neighboring susceptible tree (Bak & Tang, 1990), this is not always the case in other examples. In epidemiology, for example, a disease propagates depending on the contagiousness of the disease (Easley & Kleinberg, 2010): a disease such as Ebola is more contagious than chlamydia as Ebola is airborne whereas chlamydia only transmits through sexual contact. Ebola shall therefore have a higher probability of infection than chlamydia when two agents meet.

In innovation sciences, the propagation of awareness is related to neutral WOM. The probability of propagation of awareness is dependent on both the relationship between two consumers as well as the observability of the innovation. i.e. Awareness propagates more easily to a close friend compared to a far friend simply because of the intensity of their contact, and awareness of a mobile phone spreads easier compared to the installed applications, as the mobile phone has a higher observability. For modelling purposes, however, a distinction between continuous and discrete probabilities is made. In the previous examples, the probability behaves continuously and can take any value between 0 and 1. In a discrete model, however, the probability of propagation is either 1 (propagation) or 0 (no propagation) which is represented in the presence (probability of 1) or absence (probability of 0) of a link.

2.3. Seeding strategies

Showing the positive impact of increasing the number of seeds on percolation size, Vermeer (2015) has given managers and marketers a first strategy to increase percolation size. However, looking at the probability of seeds being placed unlucky, a second strategy can be observed. The probability of a seed to be surrounded with rejecters decreases with an increase in the number of neighbors. Therefore, seeds with many neighbors will have a lower probability of being placed unlucky compared to seeds with a few neighbors. The number of neighbors of an agent is also known as the degree centrality of an agent: agents with a high number of neighbors are considered to have a high degree centrality. Centrality is a measurement which defines the importance of a seed in a network (Freeman, 1978). Centrality, however, can also be measured by other characteristics than the number of neighbors. Examples are eigenvector centrality, betweenness centrality and closeness centrality (Wilenski, 2013).

Although eigenvector centrality is a measurement related to the number of neighbors, its value is not based upon the number of neighbors of the agent in question, but on the degree centrality of its neighbors. An agent with a high eigenvector centrality is an agent who has a lot of neighbors with high degree centrality. Being connected to these important agents makes an agent also important in the network. Betweenness centrality, however, relates to the number of times an agent is on the shortest path between other agents. A shortest path is the path which requires passing the least agents when information propagates from one agent to another. Betweenness centrality is calculated as follows: *[…] you take every other possible pairs of turtles [agents] and, for each pair, you calculate the proportion of shortest paths between members of the pair that passes through the current turtle [agent]. The betweenness centrality of a turtle [agent] is the sum of these."* (Wilensky, 2013, betweenness-centrality). Finally, closeness centrality is a measurement of the average distance of the shortest paths from one agent to all other agents. The agents which has the lowest average distance to all other agents in the network, has the highest closeness centrality.

2.4. Consumer adoption

Consumers adopt an innovation when they have a positive pre-purchase attitude towards the innovation (Oliver, 1980; Rogers, 2003). This attitude is based upon expectations coming from personal, commercial, public and experiential sources of information. Especially the personal sources have a significant impact, since they not only inform the consumer but also legitimize the information (Oliver, 1980; Kotler & Armstrong, 2010). Positive information (PWOM) may lead to a higher pre-experience attitude and thus can enhance diffusion, whilst negative information (NWOM) may result in a lower pre-experience attitude and hamper further diffusion.

After their purchase, consumers have a post-purchase attitude based upon their experiences (Oliver, 1980). The outcome of a post-purchase evaluation can either meet, fall short or exceed expectations outcome resulting in either satisfaction or dissatisfaction, the most important sources for PWOM (Brown et al., 2005) and NWOM (Bearden & Oliver, 1985) respectively. Satisfaction is defined as *"[…] the consumer's fulfillment response. It is a judgment that a product/service feature, or the product or service itself, provided (or is providing) a pleasurable level of consumption-related fulfillment, including levels of under- or overfulfillment"* (Oliver, 2015, p8), where for dissatisfaction the word unpleasant should be substituted for pleasurable.

A second source of NWOM, is NWOM expressed by rejecters. By definition, their negative assessment of an innovation does not stem from a difference in pre- and post-purchase attitude due to a negative experience with consuming an innovation. Instead, rejecters can spread NWOM when they evaluated the price of an innovation against their own attitude, and found the innovation of too low quality or too expensive (Bearden and Oliver, 1985). Focusing on rejecters is especially interesting as an extension of ABMP, as rejecters in the standard model of neutral WOM are completely passive and play no role whatsoever except that rejecters do not spread information to their neighbors. By analyzing how rejecters can still affect the attitude of potential adopters towards an innovation, we gain insight in how NWOM hampers diffusion and what effective price and promotion strategies can look like to cope with NWOM.

2.5. Modelling Word-of-Mouth

2.5.1. Simple propagation in Agent Based Modelling of Percolation

The advantage of an ABM compared to other methodologies is that agents behave according to their own attitudes. In ABPM agents have a set of decision rules which defines behavior whether to adopt or reject. The most basic adoption rules in ABMP are the ones where the agent compares his or her preference with a characteristic variable of the information received. This information can come in many forms, such as quality or price. Solomon et al. (2000) and Goldenberg et al. (2000) assume that agents have an attitude which is expressed in their Minimum Quality Requirement (MQR) which they compare with the quality of the information: when the quality is equal or *higher* than an agent's MQR, the agent adopts.

Campbell (2013) and Zeppini & Frenken (2015) use a similar methodology, however, they *"[…] translate the percolation model into an explicit welfare-theoretical framework in which the inefficiency of networks can be expressed by the unfulfilled consumer surplus."* (Zeppini & Frenken, 2015, p2). Rather than expressing attitudes in MQR they express attitudes in *reservation price,* which is the maximum price a consumer is willing to pay for the adoption of information: when the price is equal or *lower* than the reservation price, agents adopt.

2.5.2. Complex propagation in Agent Based Modelling

In the previous section we have discussed different approaches to model simple propagation, ABMP however, allow to model complex propagation as well simply by extending the decision rules with PWOM and/or NWOM. In an ABM input in the decision rules can come from four different sources: 1) the agent; 2) a global value (e.g. the total number of adopters); 3) neighboring agents; and 4) the links connected to the agent.

In ABMP, the amount of PWOM and NWOM received by an agent is highly conceptualized and is often derived from the number of neighboring adopters or rejecters respectively which can be done by simply counting the number of rejecters connected to the agent. Delre et al. (2010) uses the number of linked adopters (source 3 and 4) in a utility function where utility increases with increasing number of adopting neighbors: when utility reaches a minimum required utility (source 1), the agent adopts. Mas Tur (2016) takes an approach where the MQR (source 1) decreases under the influence of linked adopting neighbors (source 3 and 4): with increasing number of adopting neighbors the MQR decreases. An interesting addition to the literature is a scaling parameter which defines the strength of NWOM for all agents modelled, expressed in the value γ (source 2). Although the value is equal for every agent, the strength of NWOM might differ between different innovations and might be dependent on different characteristics. For example a pack of gum might have less NWOM compared to a mobile phone. Furthermore, communication channels might increase the easiness to transfer NWOM from one agent to another. For example, it is might be more difficult to transfer NWOM through a written review compared to a face to face interaction. The relationship between the agents might also affect the strength of NWOM, as the advice of a good friend might be stronger than that of an acquaintance.

Focusing on NWOM rather than PWOM, Erez et al. (2004) suggest that an agent becomes less likely to adopt when neighbors reject, which results in a decrease in MQR (source 1). The strength of NWOM received by the agent is a function of the difference between the MQR of its neighbors (source 3) and the quality (source 2). The larger the difference and the more rejecting neighbors connected, the more disappointed the neighbors are, hence the increase in NWOM.

2.6. Percolation Models

Figure 6 (left) shows the results of Zeppini & Frenken (2015) on the relationship between price, network structure (in particular small world networks) and percolation size. For a fully connected network, in which every agent is informed as there are no network inefficiencies, the percolation size follows the shape of a standard linear demand curve: given reservation prices are distributed uniformly, the number of adopters is always equal to the fraction:

$$\frac{price}{maximum\ reservation\ price}$$

However, by introducing network inefficiencies by rewiring links (see 2.2.1), the percolation size decreases compared to the fully connected network. At a certain value for price, a steep decrease in percolation size is observed. This decrease is also known as *percolation threshold*. On this threshold, a small change in the price results in a large change in percolation size. Understanding the relation between a change in price, the network structure and the change in percolation size is therefore critical for managers and marketers as small change in the price might have a large impact.

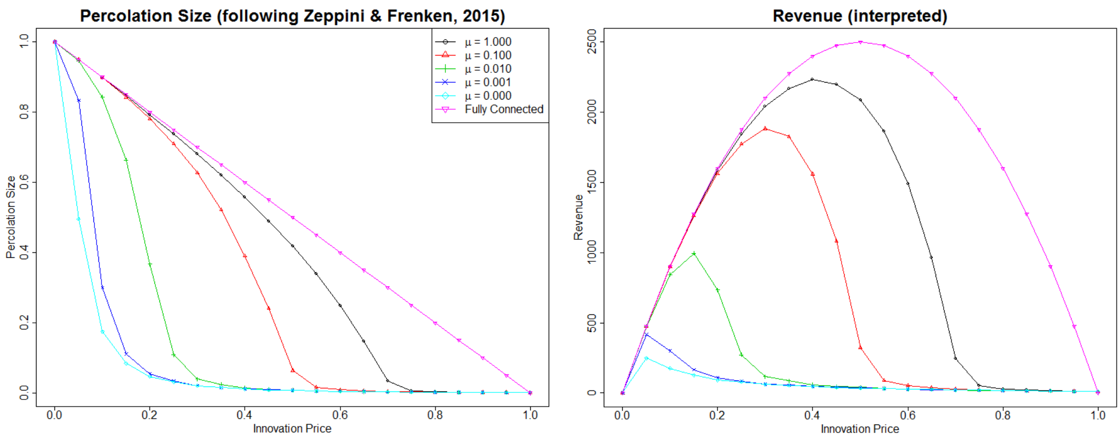


Figure 6 The relation between percolation size and revenue

Left: The results from Zeppini & Frenken (2015). Right: The revenue from the percolation size curves

2.6.1. Revenue and percolation models

Since Zeppini & Frenken (2015) study the percolation size as a function of price, the percolation size can be expressed in revenue by $revenue = percolation\ size * product\ price$. When the revenue is calculated for the results by Zeppini & Frenken (2015) (Figure 6 right), we observe that the price of maximum revenue is also a price which is in the range of the percolation threshold: a small deviation from the price where percolation diffusion has the highest revenue results in a large decrease of revenue.

3. Methodology

This research has three different aims: to analyze the effect of 1) NWOM on percolation size, 2) the effectiveness of increasing the number of seeds, and 3) the effectiveness of targeting central agents as seeds. In order to study these aims, computer simulations will be run calculating percolation size given the initial settings. As discussed before, an Agent Based Modelling approach will be used as ABM allows to include micro level behavior (agent to agent interactions such as NWOM) and network structure. The model used in this research will be an extension of the model by Zeppini & Frenken (2015) on the effect of network structure on percolation. The first step will therefore be to replicate their results with the newly created model on NWOM.

3.1. The model

In the next sections the relevant rules of the agents for this research will be discussed and how they can be translated into code.

3.1.1. Behavioral rules

As discussed in the literature review, agents have an attitude towards the adoption of an innovation. The innovation only has one characteristic, which is price P ranging from P=0 to P=1. Consumer attitude is expressed in individual reservation prices RP, ranging from RP=0 to RP=1, which indicates the 'willingness to pay' by agents.

Rule 1: agent i, will adopt the innovation if $RP_i \geq P_{innovation}$

However, whenever the price of the innovation is higher than the RP of an agent, this agent rejects the innovation and this agent is disappointed in the price. This disappointment leads to NWOM.

Rule 2: agent i will spread NWOM if $RP_i < P_{innovation}$

Under the influence of NWOM from neighboring agents of agent i, the innovation becomes less attractive to agent i. This leads to a decrease in RP_i: agent i is no longer willing to pay RP_i, but instead is willing to pay RP_i'.

Rule 3: $RP_i' < RP_i$ *under the influence of NWOM directed from the rejecting neighbors of agent i.*

The famous psychosocial law by Latané (1981) on the intensity of social forces proposes that the intensity of social forces received by an agent, in this case NWOM, is a function of the strength of the sources, immediacy of the sources and the number of sources. Furthermore Latané (1981) describes how the intensity of a social force increases decreasingly with increasing number of sources: having two rejecting neighbors result in a stronger social impact compared to having one rejecting neighbor, but the second rejecter adds less impact than the first one.

Rule 4: the strength of NWOM received by agent i increases decreasingly with additional rejecting neighbors

Note: because the results of the model will be compared to that of Zeppini & Frenken (2015), it is necessary to build in a mechanism which allows to switch between complex propagations (with NWOM) and simple propagation (without NWOM).

3.1.2. A model of social influence

Mas Tur (2016) implemented Positive Word-of-Mouth (PWOM) in an Agent Based Percolation model, studying the effect of social reinforcement. Her research suggests that agents adopt an idea when the Quality of the idea is equal to or larger than an agent's Minimum Quality Requirement (MQR). Note that the model by Mas Tur (2016) is about the adoption of an idea, where the idea is only adopted when it has a quality equal or higher than the MQR whereas this research is about the adoption of innovations where the innovation is only adopted when its price is equal or lower than an agent's reservation price.

Under the influence of social reinforcement, a phenomenon when agent i observes that neighbors have adopted the idea, agent i becomes more favorable towards adopting the idea which leads to a decrease of MQR. Mas Tur (2016) calculates this effect as follows with n being the number of neighbors which have already adopted the idea, and γ being a scaling parameter:

$$MQR_i' = MQR_i \;\; * \left(\frac{1}{n}\right)^{\gamma}$$

Note that:

- MQR_i' decreases with increasing n
- Because $\frac{1}{n}$, the increase of social reinforcement decreases for every extra n (which follows Latané, 1981).
- For γ=0 no social reinforcement is observed and allows to the model benchmark with the traditional percolation models such as Solomon et al. (2000) and Zeppini & Frenken (2015).
- For n=1, $MQR_i' = MQR_i$ as the first neighbor that adopts provides only the information that a product exists and does not provide any social reinforcement.
- Social reinforcement only occurs when an agent is informed by at least one adopting neighbor. This implies that n > 0.

3.1.3. From Minimum Quality Requirement to Reservation Price

Comparing the formula of PWOM as proposed by Mas Tur (2016) with the rules and requirements for our NWOM model, it can be observed that they behave similar. Rule 3 proposes that the reservation price decreases with increased NWOM whilst the formula suggests that MQR decreases under PWOM. Also, rule 4 proposes that the NWOM received by agent i increases decreasingly with increasing number of rejecting neighbors, whereas the social reinforcement in the formula increases decreasingly as well. Furthermore, to verify the model it is required that the model is comparable to the results of Zeppini & Frenken (2015), and by setting γ=0 this is achieved as the NWOM effect is turned off.

Although the formula is in line with all the rules and requirements for this model, it requires an adjustment. Where social reinforcement does not have any effect for only one adopter[8], it is not specified for this research that the first rejecting neighbor of an agent does not spread NWOM. Following this evaluation we can conclude that the formula proposed by Mas Tur (2016) suits this model with the following adjustment:

$$RP_i' = RP_i \ * \left(\frac{1}{1 + n}\right)^{\gamma}$$

Where n is the number of neighbors which have rejected the idea, and γ is a scaling parameter.

This function will be used in the Agent Based Model to adjust the reservation price of deciding agents. The following pseudo-code as proposed in Table 1 will be run:

t	1. Adopter propagates awareness about the innovation to susceptible neighboring agents. 2. Neighboring susceptible agents, now aware of the innovation and therefore deciding agents, seek for information about the innovation amongst neighboring agents. 3. If any of the neighboring agents is a rejecter, the reservation price of the deciding agent decreases under the influence of NWOM. 4. If the innovation price is equal or less than the decider's reservation price, the agent decides to adopt. If not, the agent decides to rejects. 5. If the agent adopts, the agent will propagate awareness about the innovation to susceptible neighboring agents. If the agent rejects, there will be no propagation of awareness.
t+1	1. … 2. …

Table 1 The pseudo-code at every time step

3.1.4. The Agent Based Model

The software used for the Agent Based Model is Netlogo (Wilensky, 1999) and the function as proposed above will be written in the programming language used for Netlogo as follows (the entire code can be found in Appendix A):

```
ask turtles with [infected-with = 0 AND (count link-neighbors with [infected-with = "adoption"] > 0)][negative-word-of-mouth]
```

```
to negative-word-of-mouth
if count link-neighbors with [infected-with = "rejection"] > 0 [
      let N (count link-neighbors with [infected-with = "rejection" AND seed? != "yes"])
      set reservation-price-adjusted (reservation-price * ((1 / (1 + N) ^ gamma)))
      ]
end
```

8 $\left(\frac{1}{1}\right)^{\gamma} = 1$

All agents are asked to do the following: whenever an agent is not infected with adoption or rejection `infected-with = 0` and has one or more adopters as neighbor `count link-neighbors with [infected-with = "adoption"] > 0` continue to the part `negative-word-of-mouth`. In this part the agent is first asked whether he or she has at least one rejecting neighbors `count link-neighbors with [infected-with = "rejection"] > 0`. Next, if this is FALSE (no rejecting neighbors), the reservation price will not be adjusted, but if this is TRUE (one or more rejecting neighbors) the reservation price will be adjusted following the formula proposed in section 3.1.3. First the number of rejecting neighbors that are not seeds is stored `count link-neighbors with [infected-with = "rejection" AND seed? != "yes"]`, next the reservation price is adjusted `set reservation-price-adjusted (reservation-price * ((1 / (1 + N) ^ gamma)))`.

3.2. Benchmark of the model

To verify of the model, the results of the model without NWOM are compared to the results of the basic percolation model used by Zeppini & Frenken (2015). The ring lattice, or the regular network, from which the small world network is derived consists of 10000 nodes with a degree of 4. Reservation prices are distributed at random following a uniform, or Beta(1,1), distribution and 10 seeds are placed in the network at random.

The model by Zeppini & Frenken (2015) assumes that reservation prices are fixed and are not under influence of that of their neighbors. Rather than simple propagation, the model used in this research assumes that reservation prices are under influence of their neighbors (complex propagation). However, when γ=0 the NWOM effect is turned off[9] and the model becomes one of simple propagation.

Simulations measuring percolation size are run for Innovation Prices starting at P=0 ranging to P=1, with increments of 0.05. Every point in Figure 7 is an average value of 50 simulations. When the model by Zeppini & Frenken (2015) (Figure 7 left) is compared with the model used in this research (Figure 7 right), no differences are observed.

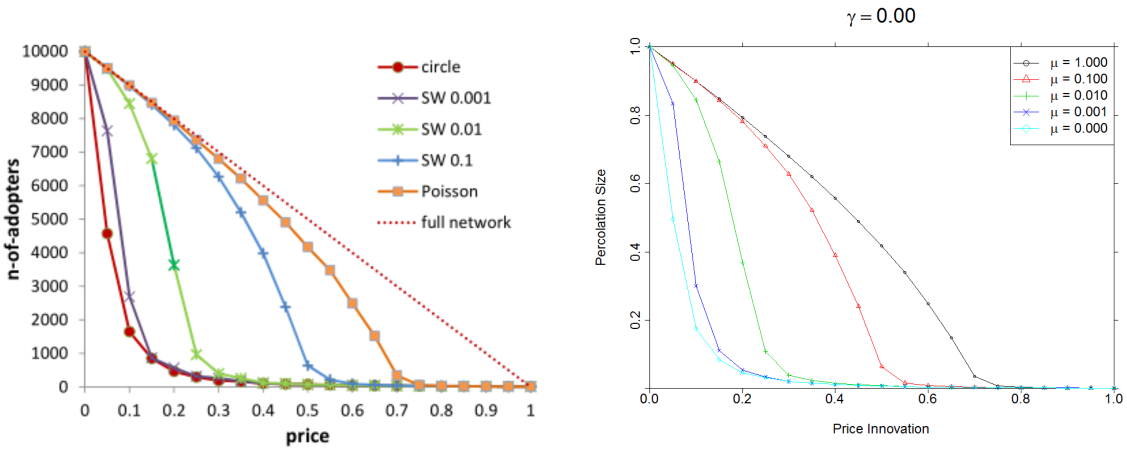


Figure 7 Benchmark of the model used in this research

Left: Zeppini & Frenken (2015, p.8). Right: Results from this research

[9] $\left(\frac{1}{1+n}\right)^0 = 1$

3.3. The effect of NWOM on percolation size

The first experiments will be run with the settings from the benchmark. The effect of NWOM will be measured for γ=0 to γ=1 with increments of 0.2 as such a graduate increase allows to study the absolute changes in percolation size given there is NWOM. Furthermore, the relative decrease in percolation size between γ=0 and γ=1 is measured to control for the effects of the network structure. The effect of randomness on the impact of NWOM will be studied by simulating percolation on small world networks with rewiring probabilities μ ∈ {0, 0.001, 0.01, 0.1, 1}.

3.3.1. The effect of randomness on NWOM

Research by Zeppini & Frenken (2015) has indicated that network structure affects percolation. To further study the effect of network structure and NWOM, we will also simulate diffusion assuming that awareness propagates both through adopters as well as rejecters. In this way, we can distinguish the effect of NWOM from the effect of network structure on diffusion. This means that every agent will be informed about the innovation (following the curve of a fully connected network) and NWOM is the only observed effect on percolation size. γ=1 (full NWOM) will be compared to γ=0 (no NWOM) to study the impact for μ=0 (low randomness / high clustering) and μ=1 (high randomness / low clustering). The settings will be equal to that of the benchmark model, although the size of the network decreases to 1000 agents and 5 seeds. This will not have an impact on the conclusions as it studies the mechanism of NWOM and is not used to compare percolation sizes.

3.4. Seeding strategies: increasing the number of seeds

The setup of these experiments is similar to the settings of the benchmark model. However, rather than using 10 seeds for this strategy the simulations will be run with different number of seeds. The number of seeds being tested will be 1, 2, 4, 8, 16, 32, 64 and 128.

Especially interesting will be analyzing the impact of a single added seed on percolation size as part of the total number of seeds. What is the impact moving from 1 seed to 2 and from 64 to 65? These experiments will compare the performance of different number of seeds with γ=0.00 (no NWOM) and γ=1.00 (full NWOM) on small world networks with rewiring probabilities μ ∈ {0, 0.001, 0.01, 0.1, 1}. The performance of a strategy regarding NWOM is measured by the relative decrease in percolation size when γ=0.00 is compared with γ=1.00.

3.5. Seeding strategies: centrality seeding

Four different centrality seeding strategies, namely degree, eigenvector, betweenness and closeness centrality (see section 2.3. for definitions), will be compared to a random seeding strategy. A random strategy implies that seeds are randomly picked, which requires little resources, whereas a centrality strategy requires the *selection of seeds* which therefore requires more resources compared to a random strategy. When aimed for high percolation size, a centrality strategy is therefore only useful if it has a higher percolation size compared to the random strategy. Regarding the performance of a centrality seeding strategy under NWOM, the performance is measured by the relative decrease in percolation size when γ=0.00 is compared with γ=1.00.

These experiments will be done on small world networks with rewiring probabilities $\mu \in \{0, 0.001, 0.01, 0.1, 1\}$. Because computing centralities requires a lot of processing power, the amount of nodes is reduced to 5000[10]. The number of seeds is reduced accordingly to 5.

3.6. Quality indicators

In order to ensure the reliability of this research, two questions have been asked: 1) 'did I build the model right?', and 2) 'did I build the right model?'. To answer these questions, the model and the simulation setup are therefore verified and validated (Pace, 2004). This research follows the guidelines of Rand and Rust (2011) on verification and validation and the model and the simulation setup will be reviewed next.

Verification, or the extent to which the model correspondents with the conceptual model, is ensured by having critical parts of the code checked by other researchers (such as the code on adoption and rejection) and by using the approach from existing models. Furthermore, the models are tested with extreme values, to test whether the results still make sense. Iterations are introduced step by step allowing to check for any unexpected behavior. The first iteration from the basic model is introducing NWOM to the basic model. Next, the basic model will be changed in two ways: 1) simulations are run with different number of seeds keeping the other setting equal; and 2) simulations are run with different centrality seeding strategies keeping the other settings equal.

Validation, or the extent to which the model correspondents with reality, is ensured by checking the face-validity of the processes at the micro and macro level. Adoption is a function of a consumer's attitude, captured in his or her reservation price, and the effect of received NWOM. Generalization of the individual decision making process is limited, as reservation prices are distributed at random and the strength of NWOM is highly conceptualized. The aim of this research, however, is not to increase our understanding of individual behavior at the micro level, but to study the effects of social network interactions, in particular NWOM, on limiting diffusion of innovations, and the effectiveness of marketing strategies that can minimize the potential negative effects. More specifically, the aim of the research is not to make predictions of a specific *outcome* of the introduction of an innovation in a social network, but to study how percolation size is affected by NWOM, for different network structures. However, since modelled on small-world network, the results can be interpreted for practical use as small-world networks can be considered as being closest to real-market situations.

Finally, results of the simulation should also be reliable. Because the setup of the model is a random process, the results are not always be the same when the simulations are repeated. Therefore, to ensure the reliability of the results of a single setup, it is repeated 50 times and average value of these simulations is reported.

[10] Note: with this reduction the simulations took about 240 hours (10 days!) of non-stop calculations on a computer with 16gb of RAM and an Intel i7 processor with 8 cores.

4. Results

4.1. To what extent does NWOM affect percolation size?

In this section the impact of NWOM on percolation size will be discussed. Furthermore, the relation between the network structure (clustering and randomness) will be analyzed.

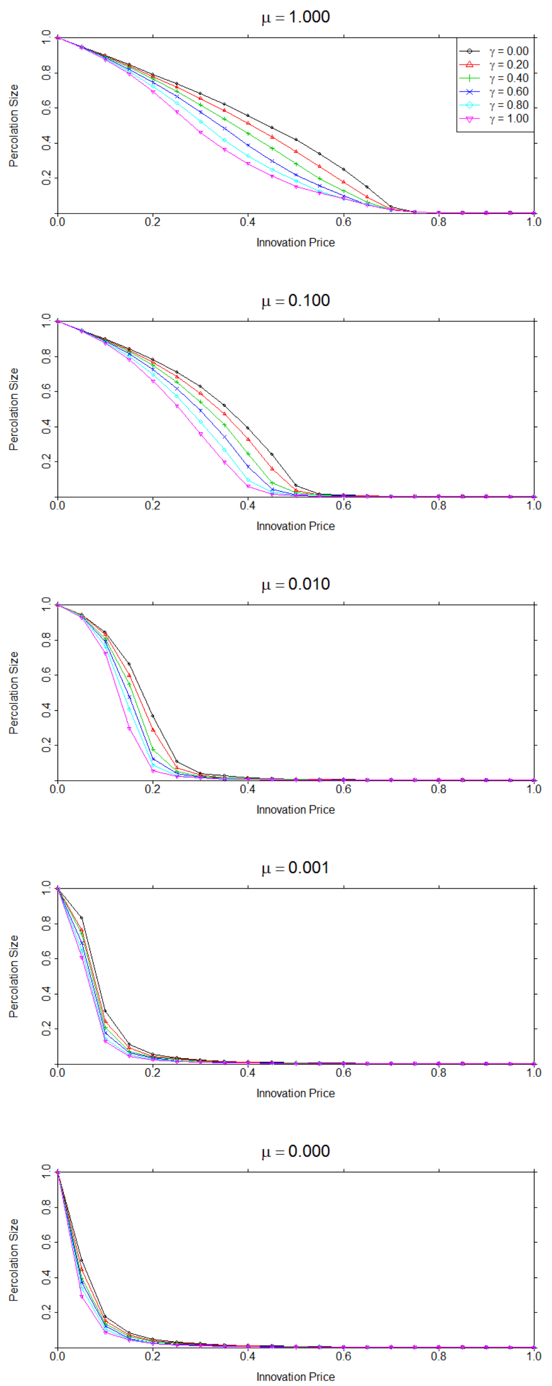


Figure 8[11] An increase of NWOM strength on different network structures

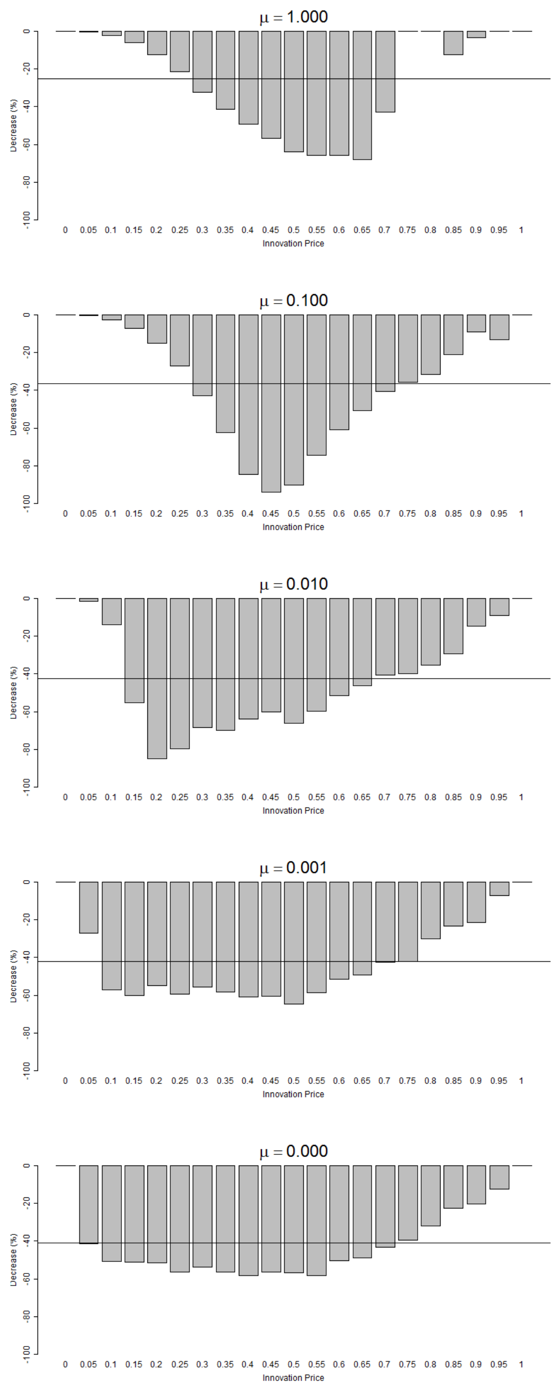


Figure 9 The relative decrease in percolation size

Measured in % from γ=0.00 to γ=1.00. The horizontal line is the mean decrease for the respective network structure.

[11] 10000 agents, 10 seeds at random, awareness propagates from adopters

Figure 8 shows the impact of an increase in γ on the percolation size. First of all, with an increase in γ a decrease in percolation size is observed, implying that agents which initially had a positive attitude towards adoption, have rejected under the influence of NWOM. This decrease in percolation size reshapes the percolation threshold increases the steepness of the threshold. Due to this increase of steepness, a deviation from the Innovation Price for maximum revenue (see section 2.6.1.) therefore leads to a larger decrease in revenue given there is NWOM as opposed to situation without NWOM.

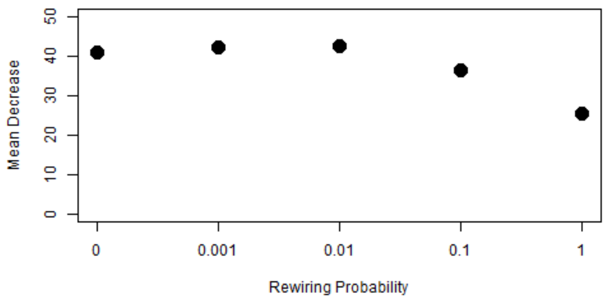


Figure 10 Mean decrease of Figure 9 (in %)

Regarding the impact of the network structure on NWOM, it can be observed that the absolute decrease in percolation size is the largest for random networks since the vertical distance between the data points (an increase in γ) is the largest, and the lowest for regular networks (Figure 8). However, when the relative decrease in percolation size is observed in Figure 9 it is observed that the decrease is lowest for random networks and the largest for regular networks instead. The shape of the mean relative decrease in Figure 10 is the same as the increase in clustering in Figure 3 (see page 11). This observation is in line with research by Mas Tur (2016) concluding that the strength of social reinforcement (in this case NWOM) increases with clustering.

4.1.1. The effect of randomness on NWOM

In this section we will further explore what mechanisms cause the reinforcing effect of clustering on NWOM. This will be done by assuming that awareness both propagates from adopters as well as rejecters, allowing to completely turn off the effect of network structure on percolation size and only observe the effect of network structure on NWOM.

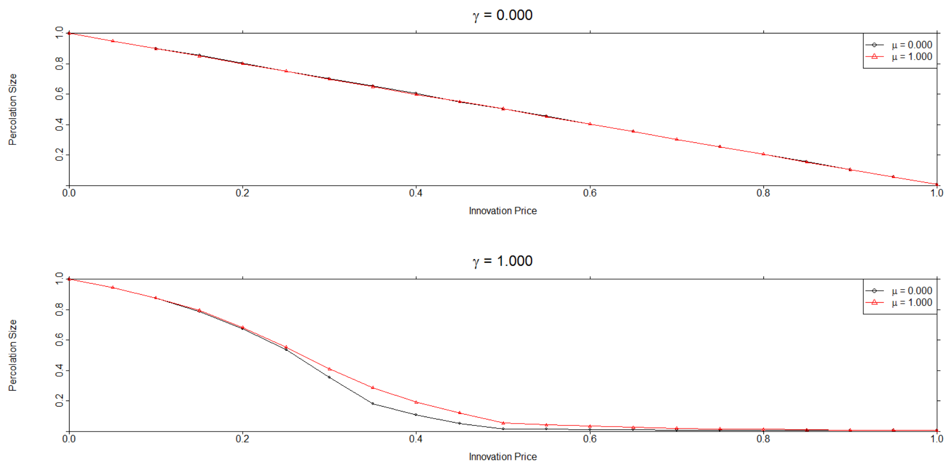


Figure 11 Percolation with 100% awareness[12]

<u>Top:</u> diffusion in a fully clustered as well as a random network where both adopters as well as rejecters propagate awareness, without NWOM. <u>Bottom:</u> A similar network, but with NWOM

Looking at Figure 11 for γ=0 (top) the percolation size is equal to that of a fully connected network for both μ=1.000 as well as μ=0.000, meaning that awareness diffusion on both the random network as well as the clustered network is not limited by network inefficiencies. When NWOM is added to the system by setting γ=1.00 (Figure 11 bottom) a decrease in percolation size is observed for both network structures, but with a larger decrease for the clustered network (μ=0.000) compared to the random network (μ=1.000). This validates our previous results reported in Figure 8 - Figure 10. In the next section it will be discussed what the possible mechanism is behind this observation.

Previously we have mentioned three different groups of agents: adopters, rejecters and susceptibles. Every agent in the network is in one of these states. For complex propagations however (the influence of NWOM on the decision process) the agents can also be considered to be an affected agent or new rejecter. An affected agent has one or more rejecting neighbors during the decision phase (see 2.1) and can both be an adopter as well as a rejecter. An affected agent can be identified by the fact that its adjusted reservation price (the reservation price adjusted for NWOM) is lower than its initial reservation price. Furthermore, a new rejecter is an affected agent having a reservation price higher than the innovation price but an adjusted reservation price which is lower than the innovation price. This agent used to be an adopter, but under the influence of NWOM the agent became a new rejecter.

[12] 1000 agents, 5 seeds at random, awareness propagates from adopters and rejecters

A decrease in percolation size given there is NWOM is the result of an increase in the number of new rejecters. An increase can be explained by 1) an increase in the number of new rejecters amongst the affected agents, whilst the number of affected agents remains equal (Figure 12 center); 2) an increase in the number of affected agents with the ratio of new rejecters and affected adopters remaining equal (Figure 12 right); and 3) a combination of 1 and 2. The first implies that affected agents are connected to more rejecters during the decision phase which results in a stronger decrease in reservation price amongst the affected agents and an increase in the number of new rejecters, whilst the second implies that more deciding agents have neighboring rejecters which results in an increase in the number of affected.

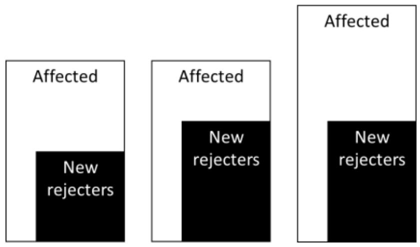


Figure 12 An increase in new rejecters

Left: original. Center: ratio affected / new rejecters changes, number of affected equal. Right: ratio equal, increase in number of affected

An increase in the number of affected agents can be measured by observing the number of agents having a higher reservation price as a susceptible agent compared to their reservation price as an infected agent. Next, the average number of rejecting neighbors can be measured by observing the average adjusted reservation price (because the difference between reservation price and adjusted reservation price is dependent on the number of rejecters when an agent decides) amongst the affected agents: if the average number of rejecting neighbors of affected agents increases, the average adjusted reservation price amongst that group decreases.

Observing the results in Figure 13 (bottom) indicates that the average reservation price amongst the affected agents is slightly lower in clustered compared to random networks. Since a lower average reservation price can only be observed when the average number of rejecters connected with deciders is higher, this is in line with the conclusions by Mas Tur (2016) on the support of clustering links on social reinforcement. However, an increase in the group of affected is observed (Figure 13 top) in the clustered network as compared with the random network as well, implying that more agents have rejecters as neighbors during the decision phase. In Appendix B the role of shortcuts regarding the results of Figure 13 are discussed.

Figure 13 The mechanisms of NWOM

Top: the number of agents whose reservation price has decreased under the influence of NWOM. Bottom: The average adjusted reservation price for these affected agents. For price = 0.0 there are no affected agents since every agent adopts

4.2. Seeding strategies: increasing the number of seeds

In the previous section the negative effects of NWOM on percolation size have been identified. In this section the question will be answered on whether managers and marketers can do something about the impact of NWOM by increasing the number of seeds. Seeds here can be considered as consumers that get the product for free as part of a marketing campaign. More seeds thus implies more costs.

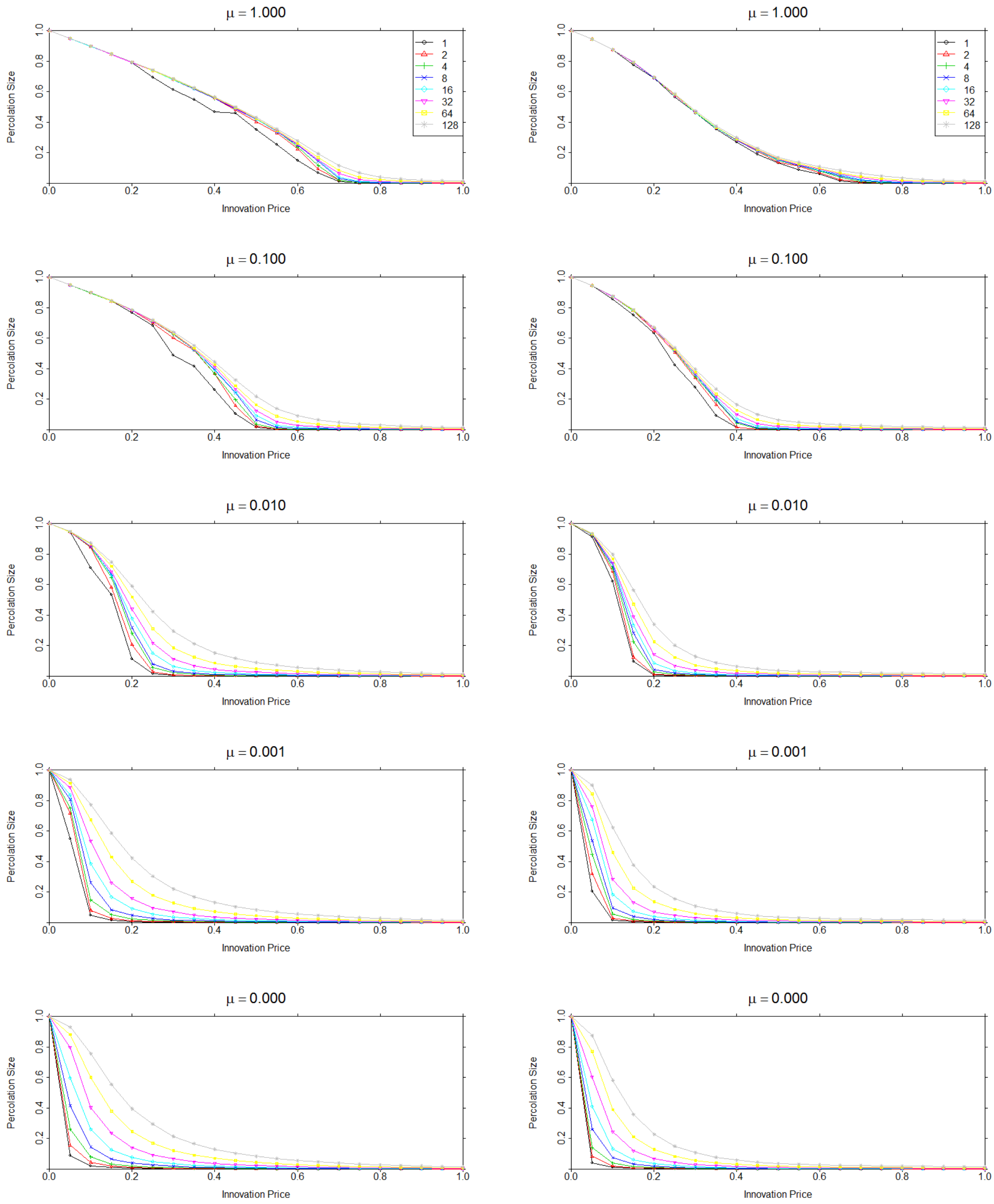


Figure 14 Percolation size when increasing the number of seeds[13]

Left γ=0.00. Right γ=1.00.

[13] 10000 agents, different number of seeds at random, awareness propagates from adopters

4.2.1. Impact seeding strategy on percolation size

The first observation of the results from Figure 14, where the percolation size for a different number of initial seeds is plotted against the innovation price, indicates that increasing the number of seeds increases the percolation size. This is because more seeds can activate more components in the operational network. Furthermore, the increase in percolation size by increasing the number of seeds has a higher impact for a high price compared to a low price. Take for example μ=1.000 (Figure 14). The percolation size of all seeding strategies is about equal up to an innovation price of 0.5. From this price onwards, the number of components in the operational network increase because less agents are willing to adopt. Because the increase in the number of components, more seeds are required to activate these components.

Figure 17, in which the mean percolation size for a seeding strategy is divided by the number of seeds used in that strategy, indicates that the return of a single seed seeds decreases decreasingly with increasing the number of seeds, meaning that an added seed is less effective compared to the previous seed. This is because with increasing number of seeds, the probability that seeds are being placed in an already active component of the operational network increases. Once a component is activated, a second seed in the operational network is redundant and the impact of the seeds on the percolation size decreases.

4.2.2. Impact of network structure on the impact of seeding strategy on percolation size

The percolation size decreases with decreased randomness (moving from μ=1.000 to μ=0.000) (Figure 14) for all different number of seeds. This is in line with the observation that the effectiveness of a seeding strategy decreases with decreases randomness (Figure 17 and Appendix D). With the number of components in the operational network increasing when randomness decreases, we observe that increasing seeds has larger effect on the total percolation size (Figure 14; Appendix E) as the vertical distance between the lines in Figure 14 increase with decreased randomness.

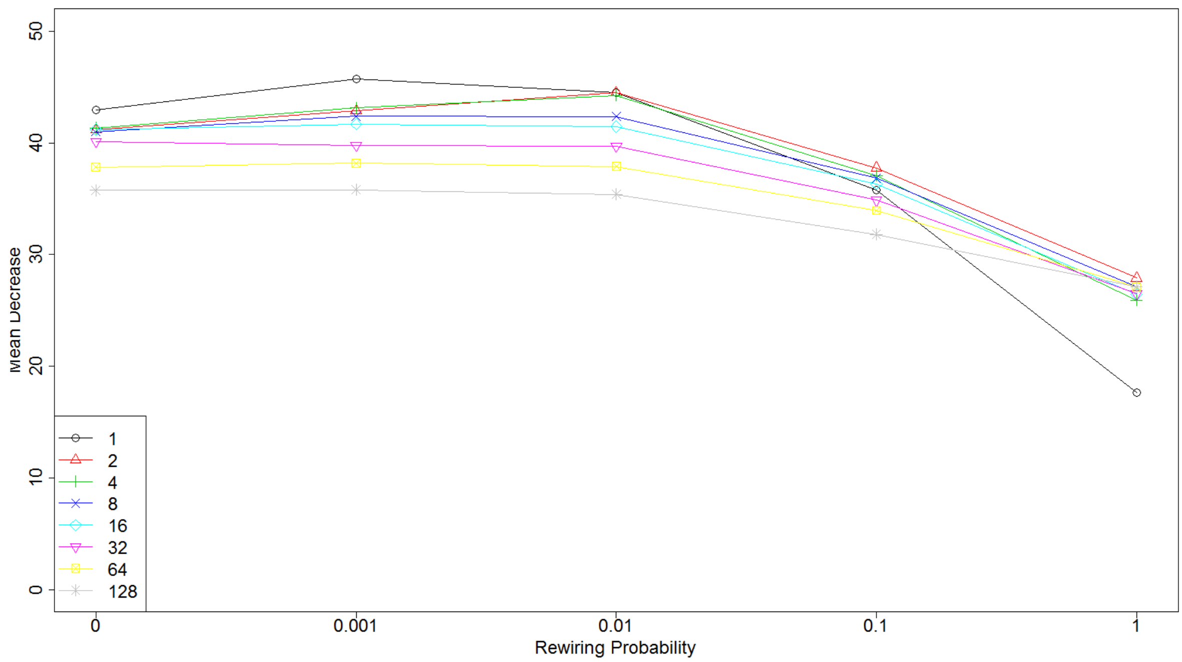


Figure 15 The effect of NWOM when increasing the number of seeds

The mean relative decrease in percolation size moving from γ=0.00 to γ=1.00 for the different seeding strategies. See Appendix H for the data points separately

4.2.3. The effect of NWOM on percolation size

Regarding NWOM, the first observation is that NWOM decreases the overall percolation size (Figure 14) since the curves for γ=1,00 are steeper. This is in line with previous observations in section 4.1. Furthermore, Figure 15 shows that the *relative decrease* in percolation size, comparing γ=0.00 with γ=1.00, decreases with additional seeds implying that the effect of NWOM for a high number of seeds is lower as compared to a low number of seeds. Furthermore, it is observed that for μ=1.000 the decrease in percolation size is almost equal.

4.2.4. Unlucky seeding

In Figure 14 it is observed that a single seed behaves significantly different compared to seeding strategies with more seeds. Moving from a single seed to two seeds has a significantly larger impact on percolation size and the percolation size of a single seed behaves less continuous compared to other strategies (Figure 14) with percolation size increasing when innovation price increases (see Appendix C) which is not observed for the other seeding strategies. As proposed previously, a possible explanation might be the result of the unlucky placement of seeds: a low number of seeds may result in the unlucky placement of all seeds. Whenever a seed is placed unlucky, the percolation size is close to 0. Such a low value often differs from the other values to a large extent and is considered to be an outlier. When calculating the combined strength of the negative outliers (a negative outlier is a value which is lower than the average value and lies on an 'abnormal' distance from the other values) in Appendix F and Appendix G (following the methodology in Figure 16), it can be observed that for few seeds strong outliers are observed on networks with high randomness (Figure 18), which is in line with our previous observations in Figure 14.

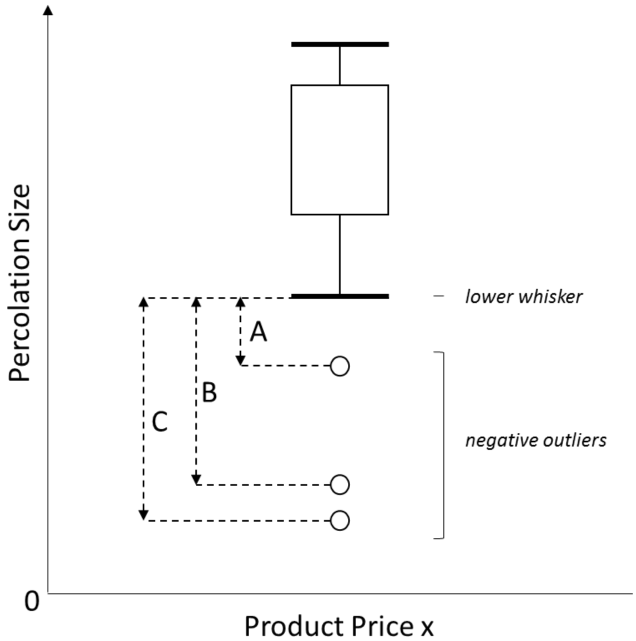


Figure 16 Methodology to calculate the strength of the negative outliers

Plotting a range of measurements as a boxplots identifies the outliers of the measurements. For every product price the combined strength of the outliers is calculated by first calculating the difference between the negative outliers and the lower whisker (A, B and C), followed by adding these values together (A + B + C). The value increases when the difference and/or the number of negative outliers increases:

$\sum(whisker_{low} - value\ negative\ outlier)$

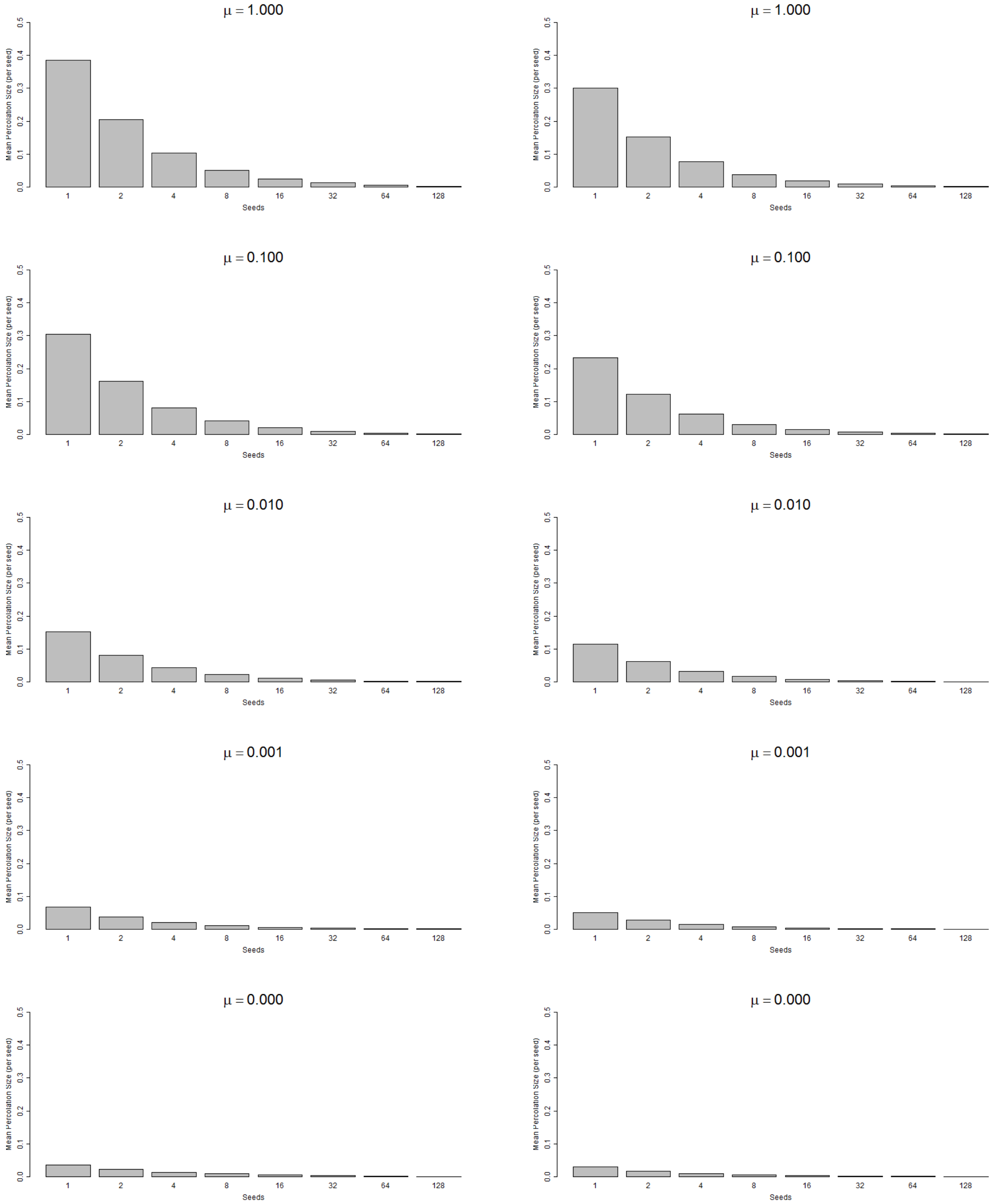


Figure 17 The impact of a single seed on the total percolation size

Following $\frac{percolation\ size}{number\ of\ seeds}$ <u>*Left:*</u> *γ=0.00.* <u>*Right:*</u> *γ=1.00*

γ	μ	seeds	0	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1
0	1.000	1	0	0				2,2	3,3	3,6	4,3	1,4	3,2	3,7									
		2	0									0,5	0,8	0,3	1								
		4	0						0						0,5	0,5							
		8	0		0		0	0								0							
		16	0		0											0							
		32	0	0		0				0			0										
		64	0	0							0				0								
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		2						0,7	1,2	0	1												
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Figure 18 The strength of outliers

Data from Appendix F and Appendix G following the methodology in Figure 16

4.3. Seeding strategies: centrality seeding

In this section the results of the experiments regarding centrality seeding will be presented. The performance of picking seeds regarding their degree, betweenness, eigenvector and closeness centrality will be discussed (for a definition of these terms, see section 2.3). First the validity of the results will be discussed, next the performance of different centrality seeding strategies with and without NWOM will be reviewed.

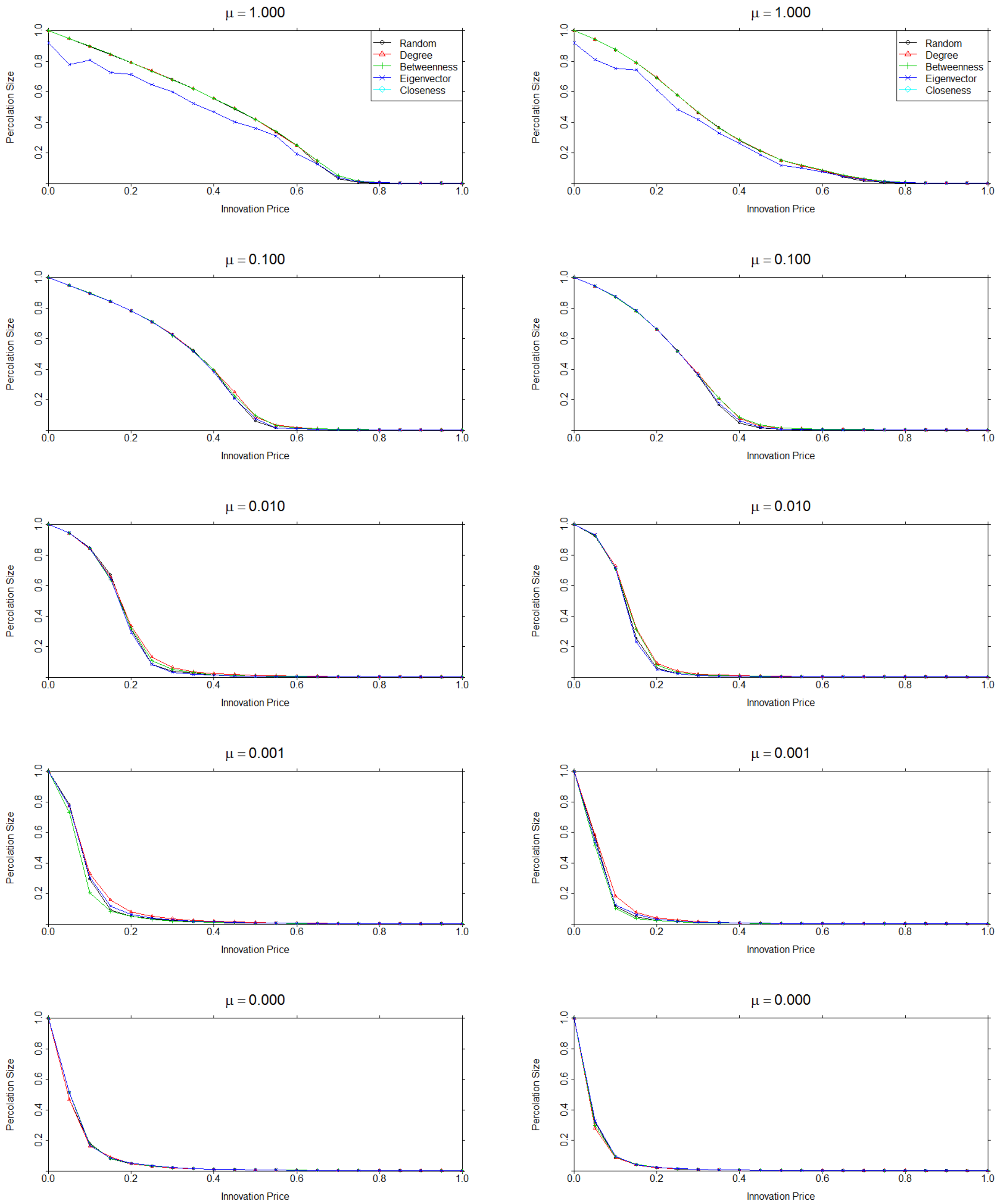

Figure 19 Percolation size for centrality seeding strategies[14]

<u>Left</u> γ=0.00. <u>Right</u> γ= 1.00

[14] 5000 agents, 5 seeds following different strategies, awareness propagates from adopters

4.3.1. False measurements

For Figure 19 the following observation can be made: except for eigenvector centrality on $\mu = 1.000$, percolation sizes are observed within a small range. The observed difference from eigenvector is not a result from the properties of eigenvector centrality, but is an issue with the software[15]. The results for eigenvector centrality on μ=1.000 are therefore invalid.

4.3.2. Impact seeding strategy on percolation size

Previous results have indicated that the percolation size of a random strategy decreases with a decreasing rewiring probability. Figure 19 indicates that this is the case for the centrality strategies as well.

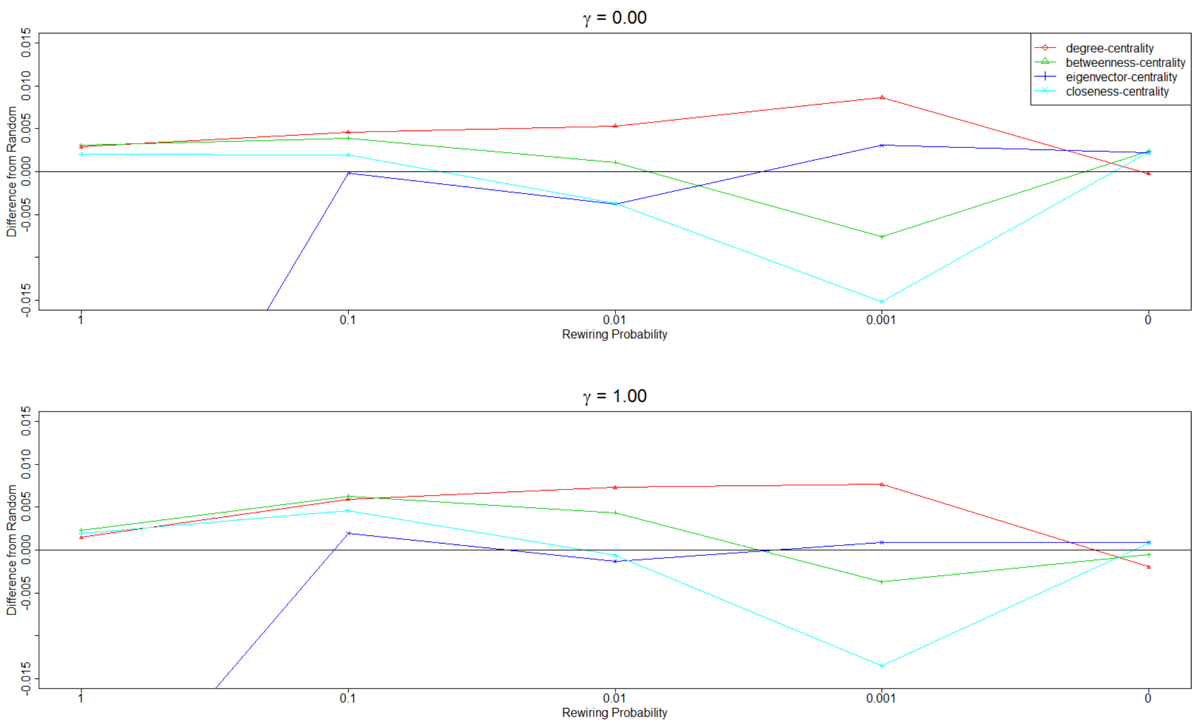

Figure 20 Mean percolation size relative to a random strategy[16]

Difference between the mean percolation size for a strategy and that of a random strategy

In Figure 20 the mean percolation size (for all innovation prices) per centrality strategy is compared to the mean percolation size of the random strategy. It can be observed that seeding strategies have no effect on regular networks since the nodes in regular networks are completely homogeneous. Every seed has an equal centrality and seeds are therefore picked at random. A similar observation is made for completely random networks where the different strategies lead to an almost equal (high) percolation size. This is due to the efficient percolation properties of a random network.

[15] Netlogo and its networks extension (nw:eigenvector-centrality) (Wilensky, 2013) does not allow to calculate the eigenvector centrality whenever there are agents without neighbors anywhere is the network. With an increasing rewiring probability the probability that a single agent has a degree of 0 increases. In cases where the number of agents with degree = 0 is equal or bigger than 1, no eigenvector centrality was calculated and no seeds were selected resulting in no percolation occurred. Since percolation size is 0, this has a big impact on the mean values. An adjustment of the Netlogo code is proposed to solve this issue, which can be found in Appendix A

[16] The mean of the percolation size of every price for every centrality seeding strategy and rewiring probability

4.3.3. Degree, betweenness and closeness centrality seeding

For μ=0.100, μ=0.010 and μ=0.001 it is observed that the values of the different strategies are very close as well. However, seeds picked following degree centrality lead to a slightly higher percolation size relative to a random strategy compared to the other strategies. Furthermore, as percolation size relative to a random strategy for degree centrality increases whilst decreases for betweenness and closeness, we observe that the difference between degree centrality on the one hand, and betweenness and closeness on the other hand increases with decreased randomness: the difference is the smallest for μ=0.100 and is largest for μ=0.001.

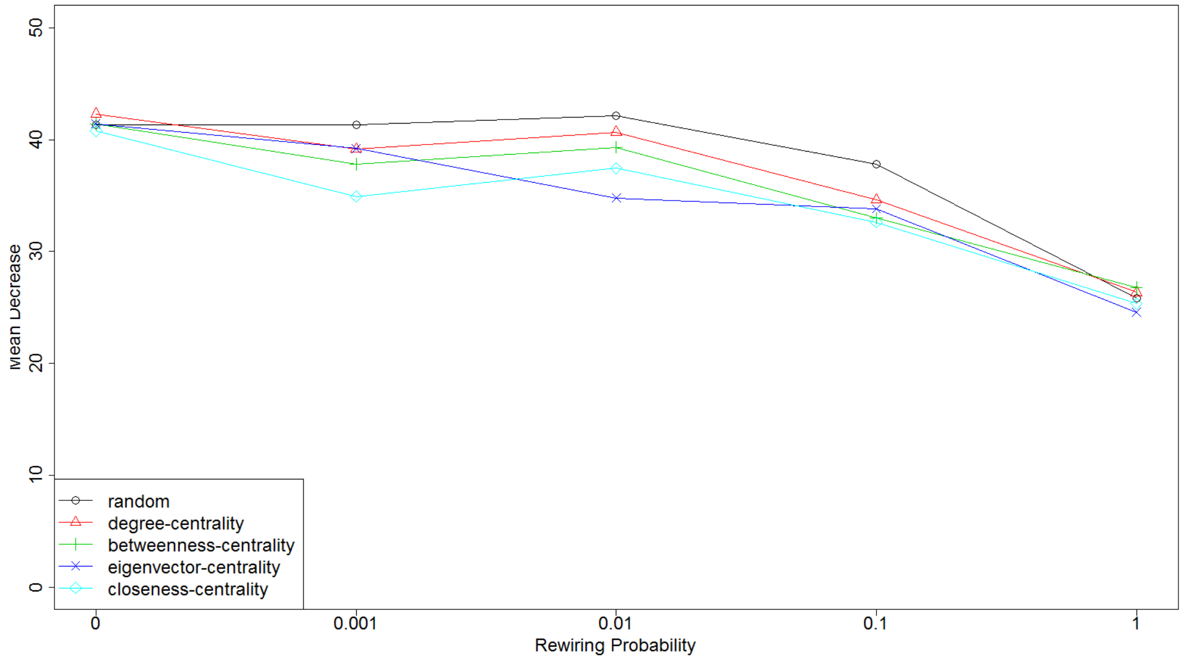

Figure 21 The effect of NWOM for different centrality seeding strategies

The mean relative decrease moving from γ=0.00 to γ=1.00 for the different seeding strategies (calculated following the approach used for Figure 15).

When observing the performance regarding NWOM (Figure 21), which is expressed in the relative decrease in the difference in percolation size for γ=0.00 and γ=1.00, we observe that betweenness and closeness centrality seeding have the lowest relative decrease whereas degree centrality has the highest decrease.

So far we have proposed that seeding strategies will lead to high percolation size when the probability for seeds being placed unlucky is low and multiple components will be activated. Furthermore, we have concluded that the impact of NWOM on percolation size decreases when awareness propagates over shortcuts. It is therefore interesting to look at 1) the number of links between the seeds. Having links between the seeds implies that they are located close to each other. When seeds are located close to each other they are limited in their ability to activate multiple components of the operational network; 2) the degree of the seeds, as a high value indicates that a seed spreads awareness to many other agents and the probability of a seed being placed unlucky decreases with increasing number of neighbors; and 3) the closeness and betweenness of the seeds, as a high value indicates that the seeds have short path lengths to other agents. Having short path lengths decreases the impact of NWOM on percolation size.

Figure 22 shows that degree centrality seeding, having the highest percolation size (Figure 20), has the lowest number of links with other seeds. This implies that seeds picked following a degree centrality seeding strategy activate multiple components in the operational network and have a low probability of being placed unlucky due to the high number of neighbors which is in line with our expectations. On the other hand, we observe that closeness, having the lowest percolation size has the highest number of links between seeds. Also betweenness centrality seeding, having the second lowest percolation size, has the second highest number of links between seeds after closeness. This is also in line with our expectations

Furthermore, whilst observing the lowest NWOM effect on percolation size for closeness and betweenness centrality seeding, we observe that these strategies have the highest betweenness centrality. This observation is also in line with earlier conclusions.

4.3.4. Eigenvector centrality seeding

We observe continuous behavior for degree, betweenness and closeness centrality regarding their percolation size: the percolation size of degree centrality seeding relative to random seeding increases with decreased randomness whereas betweenness and closeness show a decreased relative percolation size. Furthermore, the behavior of degree, betweenness and closeness centrality seeding for the relative decrease in percolation size given there is NWOM shows the same behavior: an increase from $\mu=0.001$ to $\mu=0.010$, and a decrease from $\mu=0.010$ to $\mu=0.100$.

However, the behavior of eigenvector centrality does not show any of these characteristics. Regarding percolation size relative to random seeding, we observe first a decrease from $\mu=0.100$ to $\mu=0.010$ followed with an increase from $\mu=0.010$ to $\mu=0.001$ whereas the other strategies show a continuous in- or decrease. Furthermore, the relative decrease in percolation size given there is NWOM decreases between $\mu=0.001$ and $\mu=0.010$ whereas the other strategies show an increase in relative decrease.

This observation is striking since the centrality values for eigenvector centrality seeding shows no peaks or dips relative to the other strategies on degree, betweenness, eigenvector and closeness centrality (Figure 22). We therefore need to conclude that the current review of the strategies is not sufficient to explain the behavior of the centrality seeding strategies. Possible explanations might be 1) the role of other mechanisms (one of such mechanisms is explained in Appendix I); 2) there being a nonlinear relation between the centrality values and a) percolation size; and b) the impact of NWOM on percolation size (in a way that when a with a small change in the centrality value is observed, a large change in a or b is observed); and 3) that there is no relation with the centrality values under a certain value (a threshold).

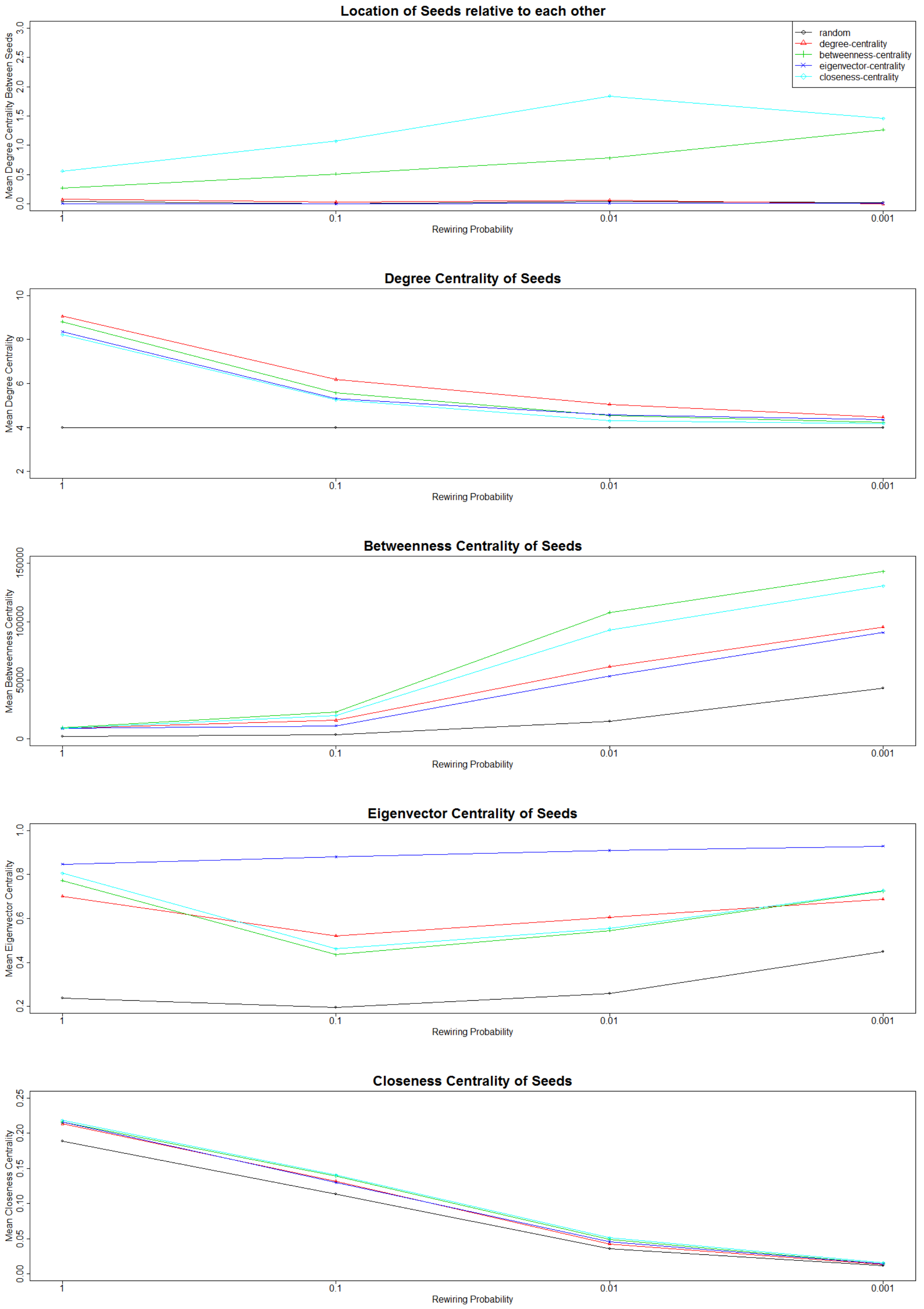

Figure 22 The location of the seeds and centrality values for the seeds[17]

[17] 1000 agents, 10 seeds, no propagation (aim is to count links between agents at t=0)

5. Conclusions

In this section the results will be presented using Causal Loop Diagrams (CLD). A CLD indicates with arrows how one characteristic affects the other. The influence can either be positive (an increase in A leads to an increase in B) or negative (a decrease in A leads to a decrease in B), which is indicated with a + or – sign on the arrow. In some CLD's loops can be identified and a distinction can be made between: 1) a reinforcing loop indicated with an R (an increase in A leads to an increase in B which leads to an increase in A); or 2) a balancing loop indicated with a B (an increase in A leads to an increase in B which leads to a *decrease* in A).

5.1. NWOM and percolation size

Research Question: To what extent does Negative Word-of-Mouth affect the diffusion size of an innovation?

NWOM leads to a decrease in percolation size and an increase in the steepness of the percolation threshold. This implies that pricing strategies are more sensitive, a small change in price leads to a large change in percolation size and revenue under NWOM as opposed to situations without NWOM. Also the impact of NWOM on percolation size is dependent on the network structure, and the CLD in Figure 23 shows these relations.

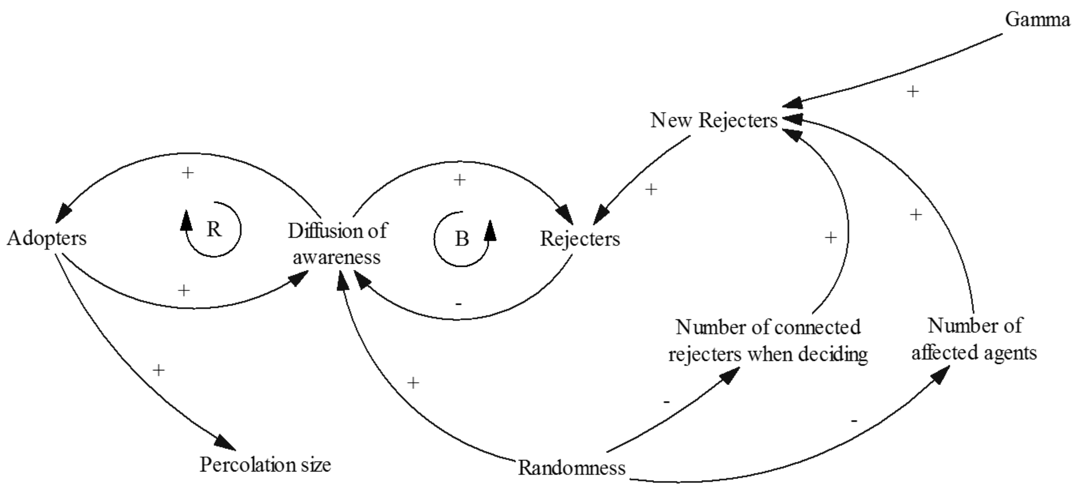

Figure 23 CLD diffusion of awareness, *randomness and NWOM*

Adopters propagate awareness of the innovation to their neighbors. These neighbors can either adopt, causing a *reinforcing loop*, or reject. Since rejecters do not propagate awareness, they limit the diffusion of awareness causing a *balancing loop*. Given there is NWOM, randomness has a positive effect on percolation size through two mechanisms: increasing the diffusion of awareness, and decreasing the number of new rejecters as the number of affected agents decreases and the number of rejecters connected to deciders decreases. Furthermore, external parameter γ has a positive effect on the number of new rejecters, which results in a decrease in diffusion of awareness and a decrease in percolation size.

5.2. Increasing the number of seeds

Question: To what extent does adding seeds change the percolation size given there is NWOM?

The main conclusion is that increasing the number of seeds increases percolation size and decreases the relative decrease in percolation size given there is NWOM. Figure 24 shows a CLD explaining the relation between the increase in the number of seeds and percolation size. It can be concluded that increasing the number of seeds has a positive effect on activating components of the operational network: the more seeds, the more components can be activated. Furthermore, increasing the number of seeds decreases the probability that all seeds are placed unlucky, which would result in low diffusion. Although adding more seeds has a positive effect on percolation size as more components are activated, with increasing number of active components the probability that a seed is placed in an already active part of the operational network increases, hence the observed decrease in effectiveness of seeds.

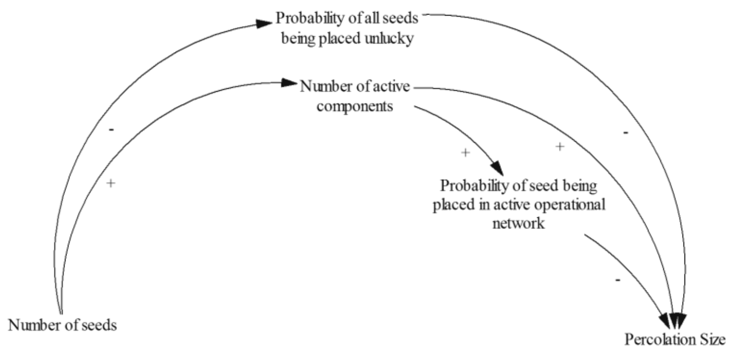

Figure 24 CLD number of seeds, effectiveness of seeds and percolation size

In Figure 25 a CLD regarding the impact of the network structure on NWOM is presented. With an increase in randomness, the number of rewired links increases. These rewired links connect different components of the operational network, decreasing the number of components but increases the size of these components. Having large components increases the probability that a seed is placed in an already active component of the network. Since a seed placed in an active component is redundant, the effectiveness of the seeds[18] decreases. However, with increasing number of components, the probability that a seed is placed inside an active components decreases, which increases the effect of a seed the total percolation size. The effectiveness of the seeds, combined with the number of seeds, defines the percolation size.

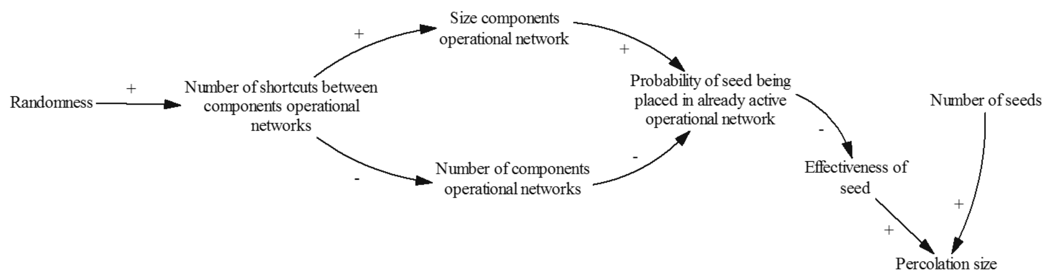

Figure 25 CLD network structure, number of seeds and percolation size

18 $\frac{total\ percolation\ size}{number\ of\ seeds}$

Regarding NWOM, it is concluded that the percolation size with a low number of seeds is affected to a larger extent by NWOM compared to the percolation size with a high number of seeds. Looking at the tree network in Figure 26, where the black agent is the seed, the probability of information reaching a second neighbor is dependent on the probability of the first neighbors being a rejecter. If the aim of the strategy is to reach a second neighbor (a goal set by e.g. researchers, managers and marketers), reaching that goal is considered to be *successful percolation*. Because NWOM increases the probability that agents are rejecters, the probability that the information from the seed reaches a second neighbor decreases. Therefore, with an increase in the number of seeds, the probability that the goal of successful percolation is reached increases. This is summarized in the CLD in Figure 27.

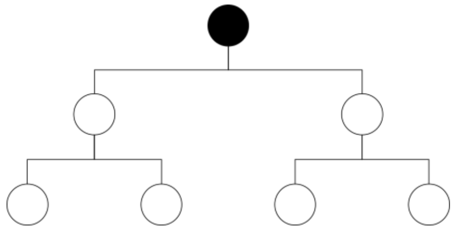

Figure 26 Tree network

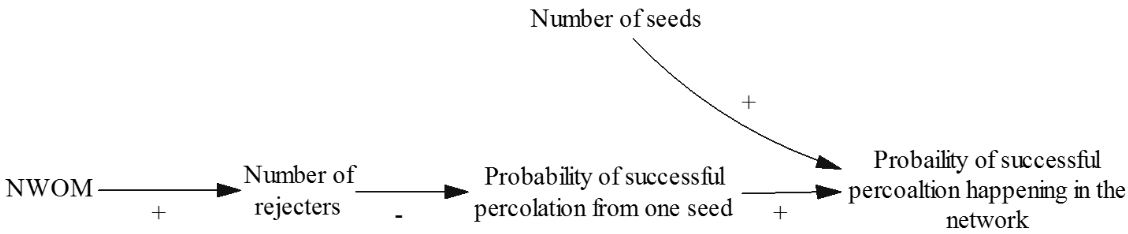

Figure 27 CLD NWOM, percolation success and the number of seeds

5.3. Centrality seeding

Question: To what extent does picking agents with high centrality as seeds change the percolation size given there is NWOM?

First of all it is concluded that centrality seeding strategies have no effect on random and regular networks: both percolation size as well as the relative decrease in percolation size under NWOM is equal for all strategies.

For the network structures μ=0.001, μ=0.010 and μ=0.100 degree centrality has the highest percolation size. Two different explanations have been proposed based upon the results for degree, betweenness and closeness centrality seeding and are visualized in the CLD in Figure 28. The first is that seeds with high degree centrality are less likely to be placed unlucky (they have a high degree) and the second is that seeds with a high number of links between them show a lower percolation size.

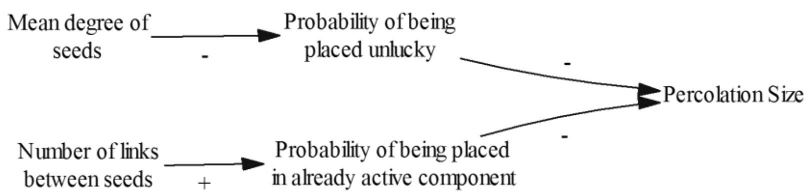

Figure 28 CLD of centrality seeding and percolation size

As for the performance of the strategies given there is NWOM, it is observed that closeness and betweenness centrality seeding have the lowest relative decrease in percolation size. This observation is in line with the conclusions proposed in section 4.1.1. that the impact of NWOM decreases with rewired nodes (Figure 29).

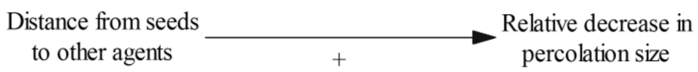

Figure 29 CLD relation between centrality seeding and relative decrease in percolation size (NWOM)

6. Discussion

This research has contributed to scientific literature as well as having practical implications for managers and marketers. First, the scientific contributions will be discussed, followed with the practical implications. Some conclusions have resulted in more questions than answers, and this chapter will finish with possible subjects for future research.

6.1. Scientific contributions

On the topic of NWOM in combination with percolation has little been written. An exception is the research by Erez et al. (2004), with the focus on *"how far it [percolation] spread across the network, in terms of the distance from the initial seed"* (Erez et al., 2004, p7). Since the distance of percolation does not coincide with percolation size (Erez et al., 2004), this research answered the question what effect NWOM has on percolation size. Furthermore, the approach of Erez et al. (2004) is limited in two ways which have been taking into account when conducting this research: first, the strength of NWOM received by an agent is dependent on the difference between the quality and the Minimum Quality Requirement. Since both MQR and the number of neighbors of an agent are defined at random, there are two random variables affecting NWOM and it is unclear to what extent either one of these variables affects percolation. This research has eliminated one of the variables as the strength of NWOM is equal for each combination of actors (agent to agent) and the strength of NWOM is only dependent on the number of neighbors (neighbors to agent). Furthermore, this research has taken socio-psychological theories into account in the behavioral rules of the ABM whereas Erez et al. (2004) have not.

The main finding of this research is that NWOM decreases the percolation size, with the strongest decrease for clustered networks. The decrease, however, does not come as a surprise. Based upon the analysis of the literature, such as the observation that NWOM leads to a decrease in sales, it was assumed that NWOM affects consumer attitude towards adoption. Based upon this principle the rules of the Agent Based Model were written. A decreasing percolation size was written into the code of the model.

A second finding relates to the relation between clustering and NWOM. These findings validate the findings of Mas Tur (2016) and provides additional insights into the mechanism which causes this relation: next to the reinforcing effect of clustering links, we have observed that rewired links decrease the social effect as these rewired links cause the diffusion of awareness to spread quickly limiting the number of new rejecters.

6.2. Practical implications

Choosing seeds with a high betweenness and closeness centrality will decrease the impact of NWOM on percolation size, however when put in practive, these seeds should be placed not based upon the centrality regarding the *entire network* (as they were in this research) but regarding the *component they are placed in.* If centrality is calculated regarding the entire network the seeds are placed close to each other (Figure 30 agent B & C) leading to low diffusion. It might prove to be more effective to select agent A and D (Figure 30) as a seed instead since they can both be responsible for the percolation of a part of the network whilst keeping the distance to the other agents short.

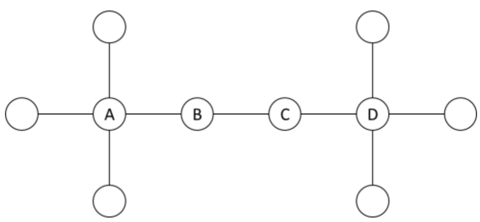

Figure 30 Betweenness and closeness seeding regarding the entire network or regarding the cluster

Furthermore, in order to reduce the relative decrease in percolation size given there is NWOM the number of seeds can also be increased. This has the additional benefit that it increases percolation size as well, just like picking seeds which have high degree centrality and which are not placed too close to each other. However, it should be taken into account that not just any number of seeds is sufficient. We have observed that with lower number of seeds, the probability of all seeds being placed unlucky increases. Although the percolation size is large in general, there is a chance of a failure of percolation when all seeds are placed unlucky. Therefore, managers should have a threshold of a minimum amount of seeds in order to reduce the probability of unexpected failed percolation. Furthermore, since the effect of every additional seed decreases while the price of a single seed remains equal, managers and marketers should take into account the ratio between expenses on seeds and the gain in percolation size (revenue). At some point adding more seeds may not prove to be effective anymore when the price of a single seed is higher than the revenue gained from increased percolation size.

As well as in this research, Zeppini & Frenken (2015) and Mas Tur (2016) conclude that percolation size decreases when price increases or quality decreases. However, this conclusion is based upon the mean values of 50 simulations. When observing the range of measurements in Appendix F and Appendix G we can observe that if a random measurement is taken from the range, there is a possibility to observe a decrease in percolation size instead when reducing the price as the lower whisker of some strategies is lower than the maximum whisker of that of an increased price. This is a limitation to the practical implications of this research.

However, in order to decrease the range of measurements and therefore the uncertainty of the outcome of a certain strategy, changing the price of the innovation might prove to be efficient. Since the price for maximum revenue is also the price at which the uncertainty of measurements is highest for μ=0.001 (this conclusion is not part of the research but can be observed in Appendix F and Appendix G), a possible pricing strategy could be to move away from this price: moving the price up or down decreases uncertainty. This implies that the outcome of a suboptimal price could lead to higher revenue compared to that of the possible outcome for an optimal price strategy. This, and the reduction of uncertainty in measurements (what strategies have smallest ranges), needs to be researched to a larger extent.

6.3. Future research

This research was not able to explain unexpected behavior regarding eigenvector centrality seeding. Both behavior related to percolation size, as well as the relative decrease in percolation size given there is NWOM, cannot be explained by the mechanisms proposed in this research: the number of links between seeds and degree of the seeds for percolation size, and the distance between the seeds and other agents regarding NWOM. Therefore further research will need to explain this unexpected behavior.

Furthermore, in Appendix I we have concluded that seeds provide protection against NWOM, however, seeds close to each other provide less protection as seeds located close to each other might have common agents they protect. Although having common agents might have a negative effect on percolation size given there is NWOM, the opposite might be the case for a network in which PWOM is the social mechanism: seeds, and therefore adopters, located close to each other reinforce their PWOM effect. It would be interesting to further research this phenomenon as it might have implications for managers and marketers regarding their seeding strategy, especially when both PWOM and NWOM are present in the network: which effect is stronger, reinforcement of PWOM or protection against NWOM?

Finally, since this research has assumed that NWOM between two agents is always equal we understand its effect on percolation size. Next the model can be extended in a way where gamma is a function of the reservation prices of an agent's neighbors based upon the approach of Erez et al. (2004). This approach would be particularly interesting when reservation prices are distributed differently, such as networks with many high or low reservation prices. Furthermore, it would be interesting to combine this with heterogeneity: agents with a similar reservation price are more interconnected[19] which would allow to test setups which are more real world like. A possible approach to adjust the reservation price is:

$$RP_i' = RP_i * \left(\frac{1}{N+1}\right)^{\gamma_i}$$

Where everything is defined as in model used in this research, except that the parameter modelling NWOM is now agent dependent. The parameter is defined as follows:

$$\gamma_i = \frac{\Sigma(P_p - P_j)}{N} \text{ for all } j \text{ such that (1) } j \text{ is a rejecter and (2) } j \text{ is a neighbor of } i$$

Notice that NWOM is now modelled by looking at the differences between the product and reservation price of neighbors of *i* who are rejecters. Notice, furthermore, that if *j* is a rejecter $P_p - P_j > 0$.

In summary, in line with empirical research of NWOM we have found that NWOM has a negative effect on percolation size. The effect of NWOM of percolation size, however, differs between different structures of the network. This implies that whilst one price or promotion strategy works fine in one situation, another strategy might be more effective in another. This is dependent on the strategic goals set by managers and marketers. Furthermore, for both science as commercial efforts, it would be highly recommended to continue research in the exiting field of innovation diffusion using percolation models. With strong processing power becoming more widely available, the models can be extended to very complex models where simulations could eventually make real world predictions.

[19] Mas Tur (2016) has applied such an approach.

7. Acknowledgements

First of all I would like to thank professor dr. Koen Frenken for being my supervisor for this research. It was fantastic, and it gave me a lot of energy, to have a supervisor as enthusiastic as you. Next, Roosmarijn Goldbach, MSc of TNO, thank you for your critical reviews and the many talks we had. Special thanks to Dr. Saeed Mohammadian Moghayer for giving me the possibility to write this thesis as an intern at the department Strategic Business Analysis at TNO. I am looking forwards to see the application of my research in practice. Furthermore, I would like to thank Dr. Frank van Rijnsoever and Dr. Jan Faber for taking the time to assess my work. Finally I would like to thank my girlfriend, mom, dad, sister, and my roommates for their guidance, reviews and support.

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9. Appendices

Appendix A Netlogo model

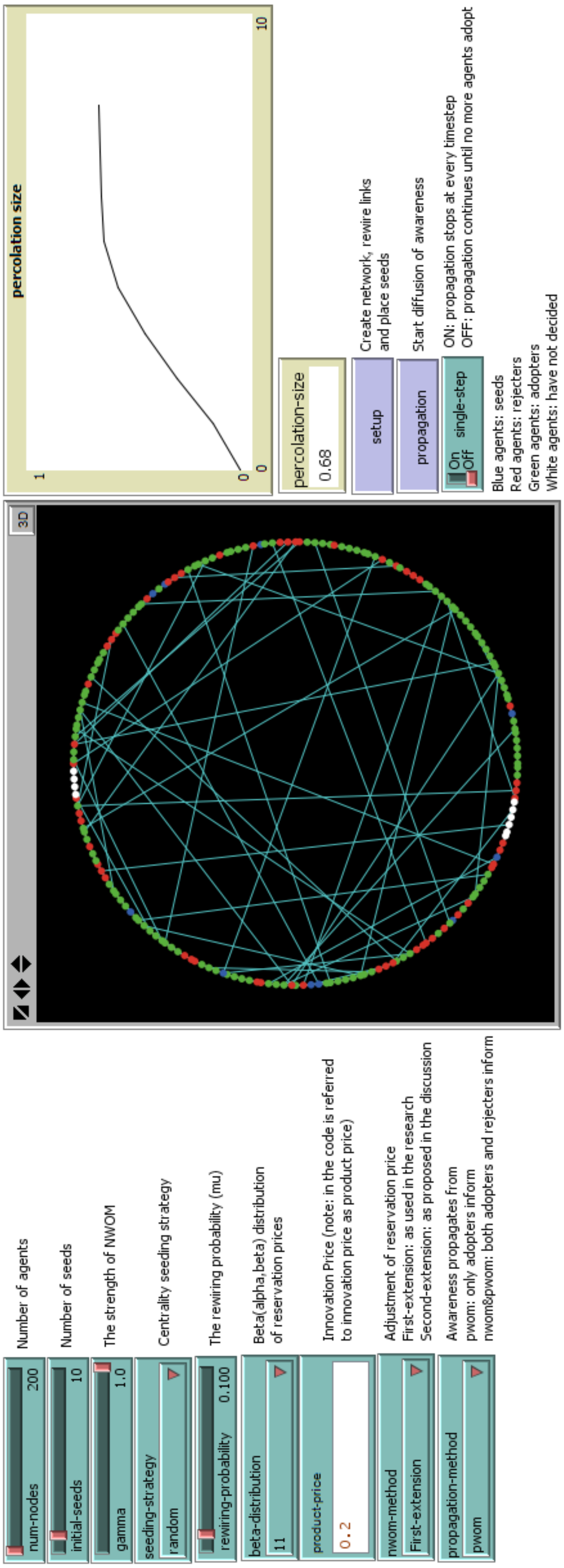


Figure 31 Screenshot of the interface of the Netlogo model

The code is an extension of the Netlogo Small Worlds Model (Wilensky, 2005)

```
extensions[
  nw
  ]

turtles-own[
  betweenness-centrality
  degree-centrality
  eigenvector-centrality
  closeness-centrality
  turtle-configurated?
  reservation-price
  reservation-price-adjusted
  seed?
  infected-with
  nwom-effect
  ]

links-own[
  rewired?
  ]

globals[
  alpha
  beta
  percolation-size
  adopters
  ]

to setup
  clear-all
  set-default-shape turtles "circle"
  reservation-price-distribution
  make-turtles
  rewire-all
  ;this line would fix the problem with eigenvector centrality for μ=1.000 but would
drastically decrease simulation speed (TESTED)
  ;if [eigenvector-centrality] of one-of turtles = FALSE [setup]
  ;this line could work as well (NOT TESTED)
  ;ask turtles [set degree-centrality count link-neighbors]
  ;if [degree-centrality] of one-of turtles = 0 [setup]
  seeding
  reset-ticks
end

to make-turtles
  create-turtles num-nodes
  turtle-config
  layout-circle (sort turtles) max-pxcor - 1
  wire-them
end

to reservation-price-distribution
  if (beta-distribution = 11) [set alpha 1 set beta 1]
  if (beta-distribution = 41) [set alpha 4 set beta 1]
  if (beta-distribution = 14) [set alpha 1 set beta 4]
end
```

```
to turtle-config
  ;;beta distribution
  ask turtles with [turtle-configurated? = 0] [
  let x1 (random-gamma alpha 1)
  let y1 (random-gamma beta 1)
  set reservation-price (x1 / ( x1 + y1))

  set size 0.3
  set color white
  set reservation-price-adjusted reservation-price
  set turtle-configurated? 1
  ]
end

to rewire-all
  ask links[
    ;; whether to rewire it or not?
    if (random-float 1) < rewiring-probability
    [
      ;; "a" remains the same
      let node1 end1
      ;; if "a" is not connected to everybody
      if [ count link-neighbors ] of end1 < (count turtles - 1)
      [
        ;; find a node distinct from node1 and not already a neighbor of node1
        let node2 one-of turtles with [ (self != node1) and (not link-neighbor? node1)
]
        ;; wire the new edge
        ask node1 [ create-link-with node2 [ set color cyan  set rewired? true ] ]
        set rewired? true
        ]
      ]
    ;; remove the old edge
    if (rewired?)[
      die
      ]
    ]
end

to wire-them
  ;; iterate over the turtles
  let n 0
  while [n < count turtles]
  [
    ;; make edges with the next two neighbors
    ;; this makes a lattice with average degree of 4
    make-edge turtle n
              turtle ((n + 1) mod count turtles)
    make-edge turtle n
              turtle ((n + 2) mod count turtles)
    set n n + 1
  ]
end

to make-edge [node1 node2]
  ask node1 [create-link-with node2 [set rewired? false]]
end
```

```
to seeding
  if seeding-strategy = "random"[
    repeat initial-seeds [ask one-of turtles with [seed? != "yes"][seeds]]
    ]
  if seeding-strategy = "degree-centrality"[
    ask turtles [set degree-centrality (count link-neighbors)]
    ask max-n-of initial-seeds turtles [degree-centrality] [seeds]
    ]
  if seeding-strategy = "betweenness-centrality"[
    ask turtles [set betweenness-centrality nw:betweenness-centrality]
    ask max-n-of initial-seeds turtles [betweenness-centrality] [seeds]
    ]

  if seeding-strategy = "eigenvector-centrality"[
    ask turtles [set eigenvector-centrality nw:eigenvector-centrality]
    ask max-n-of initial-seeds turtles [eigenvector-centrality] [seeds]
    ]
  if seeding-strategy = "closeness-centrality"[
    ask turtles [set closeness-centrality nw:closeness-centrality]
    ask max-n-of initial-seeds turtles [closeness-centrality] [seeds]
    ]
end

to seeds
  set seed? "yes"
  set infected-with "adoption"
  set color blue
end

to propagation
  let percolation-size-before ((count turtles with [infected-with != 0]) / count
turtles)
  ask turtles with [infected-with = "rejection"][set nwom-effect (product-price -
reservation-price-adjusted)]
  if propagation-method = "pwom"[propagation-pwom]
  if propagation-method = "nwom&pwom"[propagation-nwom-pwom]
  let percolation-size-after ((count turtles with [infected-with != 0]) / count
turtles)
  ifelse percolation-size-after = percolation-size-before
  [
    set adopters (count turtles with [infected-with = "adoption"])
    set percolation-size (adopters / count turtles)
    ]
  [
    tick
    if single-step = FALSE [propagation]
    ]
end

to propagation-pwom
  ask turtles with [infected-with = 0 AND (count link-neighbors with [infected-with
= "adoption"] > 0)][
    negative-word-of-mouth
    ifelse reservation-price-adjusted >= product-price
    [set color green set infected-with "adoption"]
    [set color red set infected-with "rejection"]
    ]
end

to propagation-nwom-pwom
  ask turtles with [infected-with = 0 AND (count link-neighbors with [infected-with
!= 0] > 0)][
    negative-word-of-mouth
    ifelse reservation-price-adjusted >= product-price
    [set color green set infected-with "adoption"]
    [set color red set infected-with "rejection"]
    ]
end
```

```
to negative-word-of-mouth
  if nwom-method = "First-extension"[
    if count link-neighbors with [infected-with = "rejection"] > 0 [
      let N (count link-neighbors with [infected-with = "rejection" AND seed? !=
"yes"])
      set reservation-price-adjusted (reservation-price * ((1 / (1 + N) ^ gamma)))
      ]
    ]
;;this is the code to model NWOM as proposed in the discussion
  if nwom-method = "Second-extension"[
    if count link-neighbors with [infected-with = "rejection"] > 0[
      let N (count link-neighbors with [infected-with = "rejection" AND seed? !=
"yes"])
      let sum-nwom-effect (sum ([nwom-effect] of link-neighbors with [infected-with
= "rejection" AND seed? != "yes"]))
      set reservation-price-adjusted (reservation-price * ((1 / (1 + N)) ^ (gamma *
(sum-nwom-effect / N) )))
      ]
    ]
end
```

Appendix B Explanation of results section 4.1.1.

The results of Figure 13 can be explained by replicating the experiment of section 4.1.1. on a small scale (see Figure 32): on a network with 11 agents having one seed, five agents with RP ≥ P (light green) and five agents with RP < P (light red) we compare a network without rewiring (clustered) with a network with one link from the seed rewired. For the rewired network, the link removed as well as the link created (the process of rewiring) can either be to an agent with RP ≥ P or RP < P. This allows for four different scenarios: 1) red removed green created; 2) green removed green created; 3) red removed red created; and 4) green removed red created. We will assume that when repeating the experiment 4 times, every scenario will be observed once as every scenario has an equal probability of occurring.

	Not-rewired			Rewired		
#	Scenario	Number affected	Average rejecters per affected	Scenario	Number affected	Average rejecters per affected
1		4	6/4=1.5	Red removed - Green created	2	2/2=1
2		4	6/4=1.5	Green removed - Green created	2	3/2=1.5
3		4	6/4=1.5	Red removed - Red created	5	5/5=1
4		4	6/4=1.5	Green removed - Red created	4	5/4=1.25
Average:		**4**	**1.5**		**3.25**	**1.15**

Table 2 The results from the experiment

Starting diffusion from the seed at t=0, we can measure the number of rejecting neighbors for deciding agents on every time step. Furthermore the number of affected agents can be counted for every scenario. In Table 2 the results of the experiment are presented and we observe that the number of affected in the not-rewired (clustered network) is higher as opposed to the rewired network and the average number of rejecters during the decision phase (higher number of rejecters means a larger decrease in reservation price) is higher for the not-rewired as well. Both observations are in line with the observed behavior observed in Figure 13.

Next to the conclusions by Mas Tur (2016) on the reinforcing effect of clustered links, we can conclude that the effect of NWOM on percolation size is lower for rewired networks because of the positive effect of rewired links on percolation speed. The number of affected agents on a rewired network is lower as awareness spreads faster because the mean path length between the seed and the other agent has decreased. This results in a situation where more agents have decided to adopt or reject before they had any rejecting neighbors.

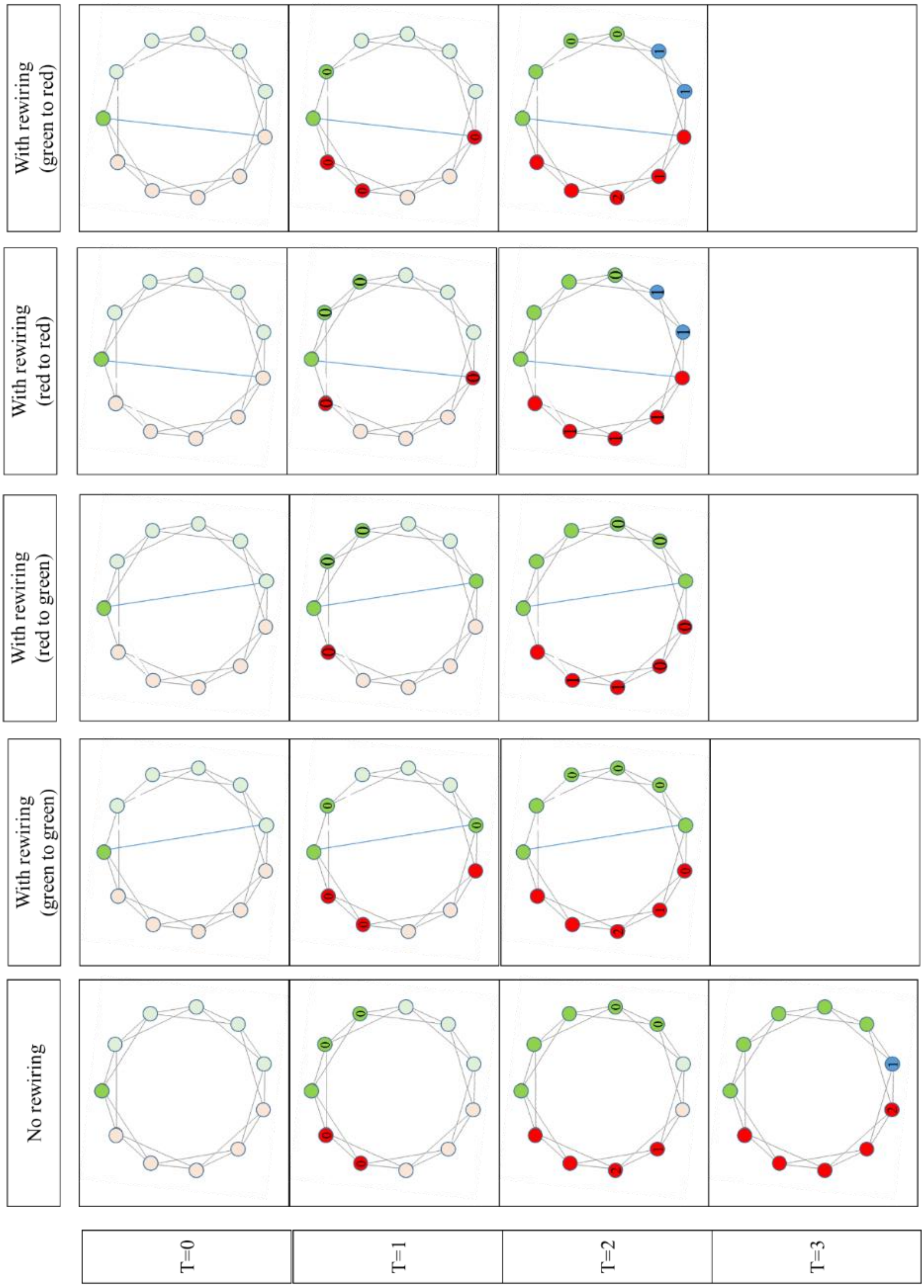
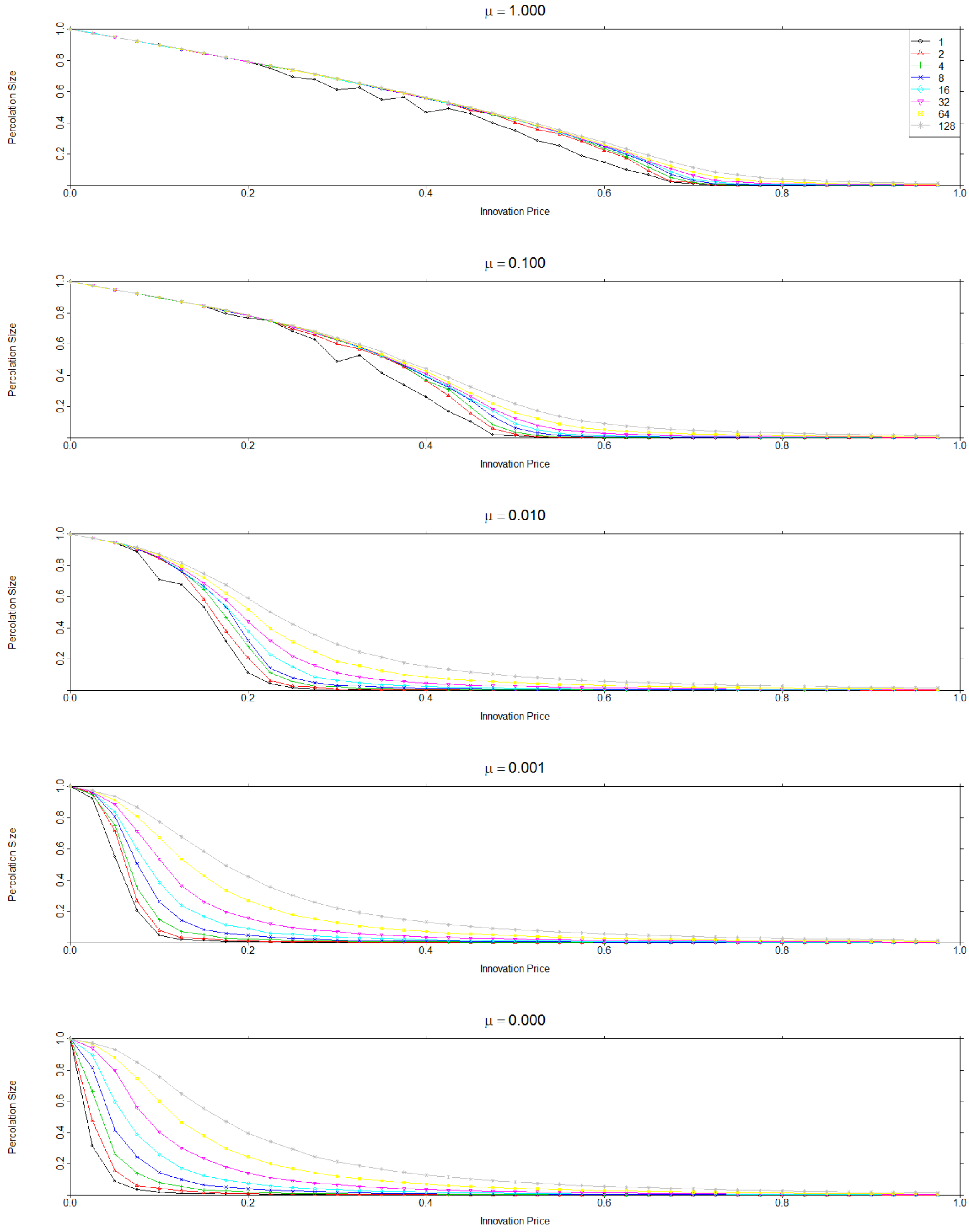


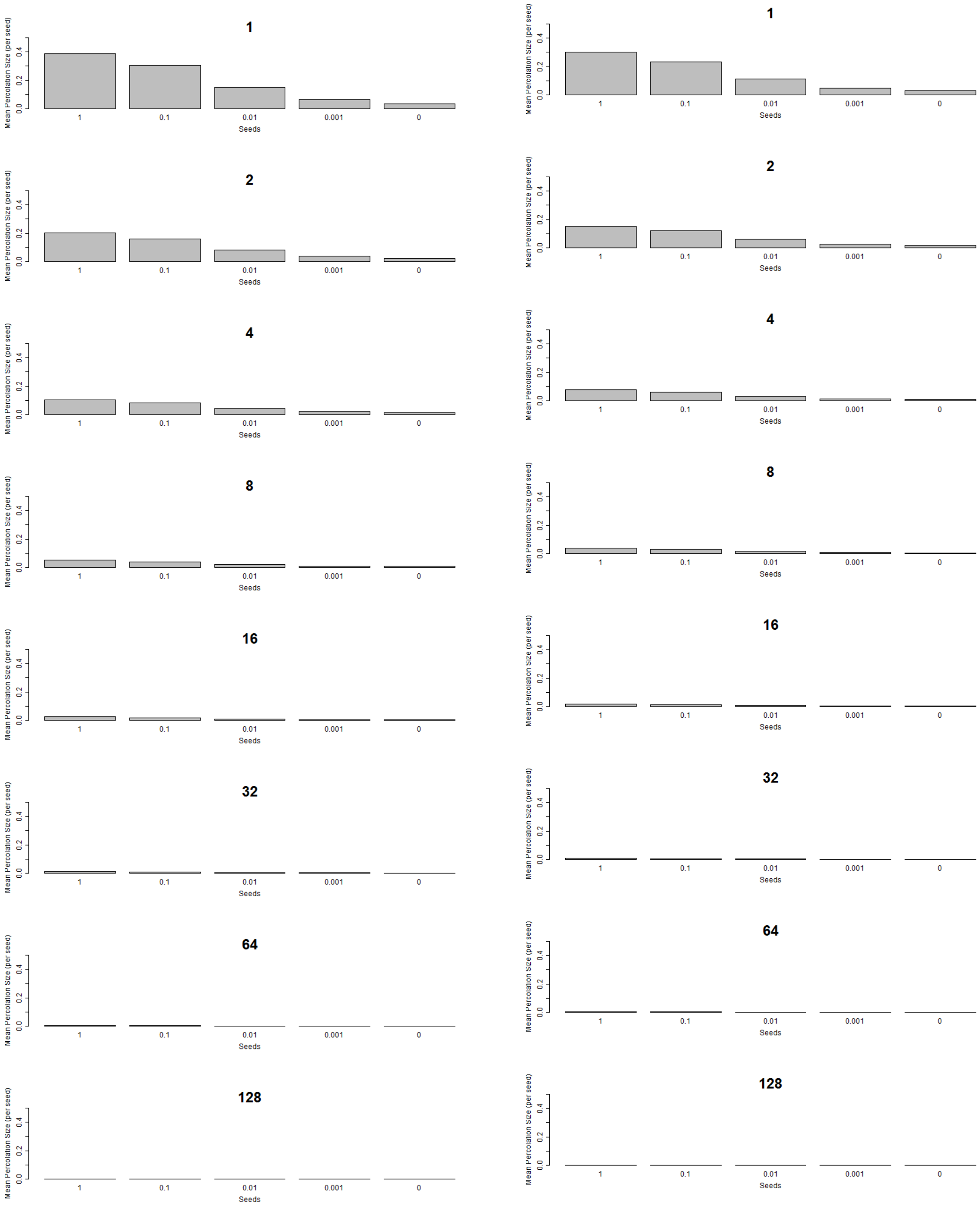
Figure 32 Small scale experiment of perclation

The difference between light green and light red agents indicates whether an agent has a positive or negative attitude. The numbers associated with the agents are the number of rejecters when the agents decide to adopt: if the number is > 0 then the agent is regarded an affected agent. Dark green and red indicate that the agent has decided between adopting and rejecting. A blue agent indicates that an agent with a positive attitude has one or more rejecting neighbors when deciding (this agent can be a new rejecter).

Appendix C Figure 14 (left) with more data points

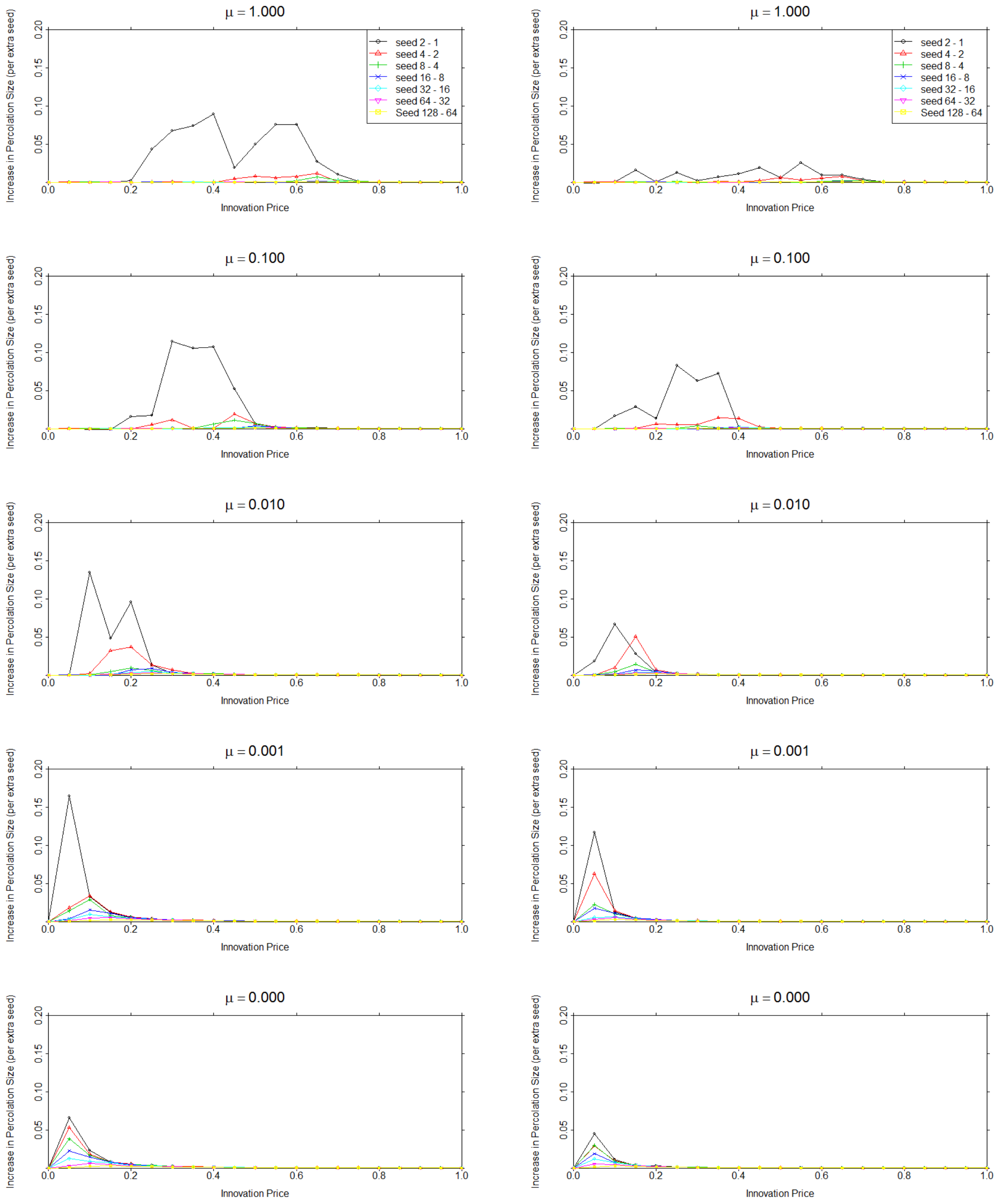


Appendix D Alternative view of Figure 17



Left γ=0.00. Right γ=1.00

Appendix E The change in percolation size per seed of figure 11

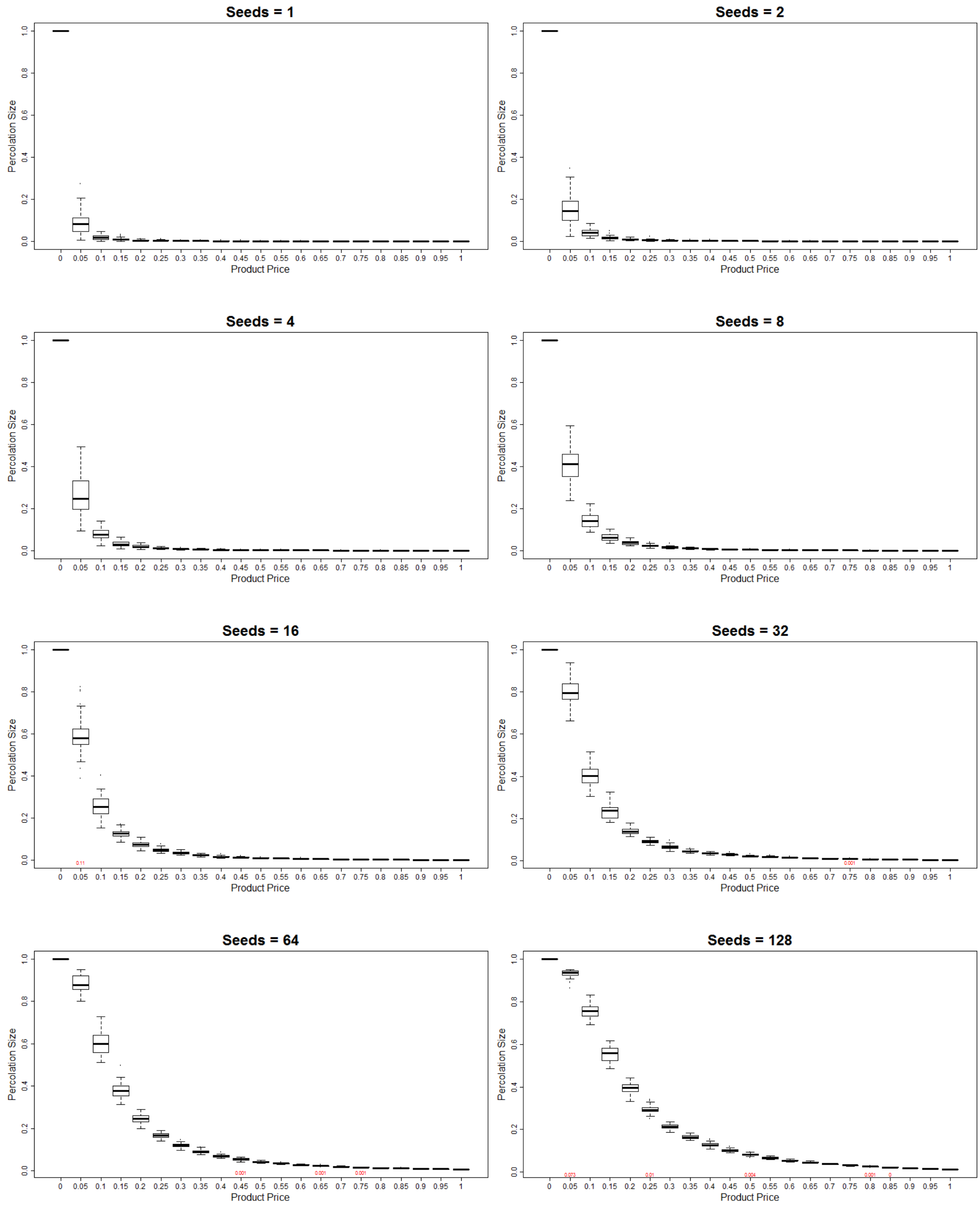


Following: $\frac{\Delta percolation\ size}{\Delta number\ of\ seeds}$*. <u>Left</u>* γ*=0.00. <u>Right</u>* γ*=1.00*

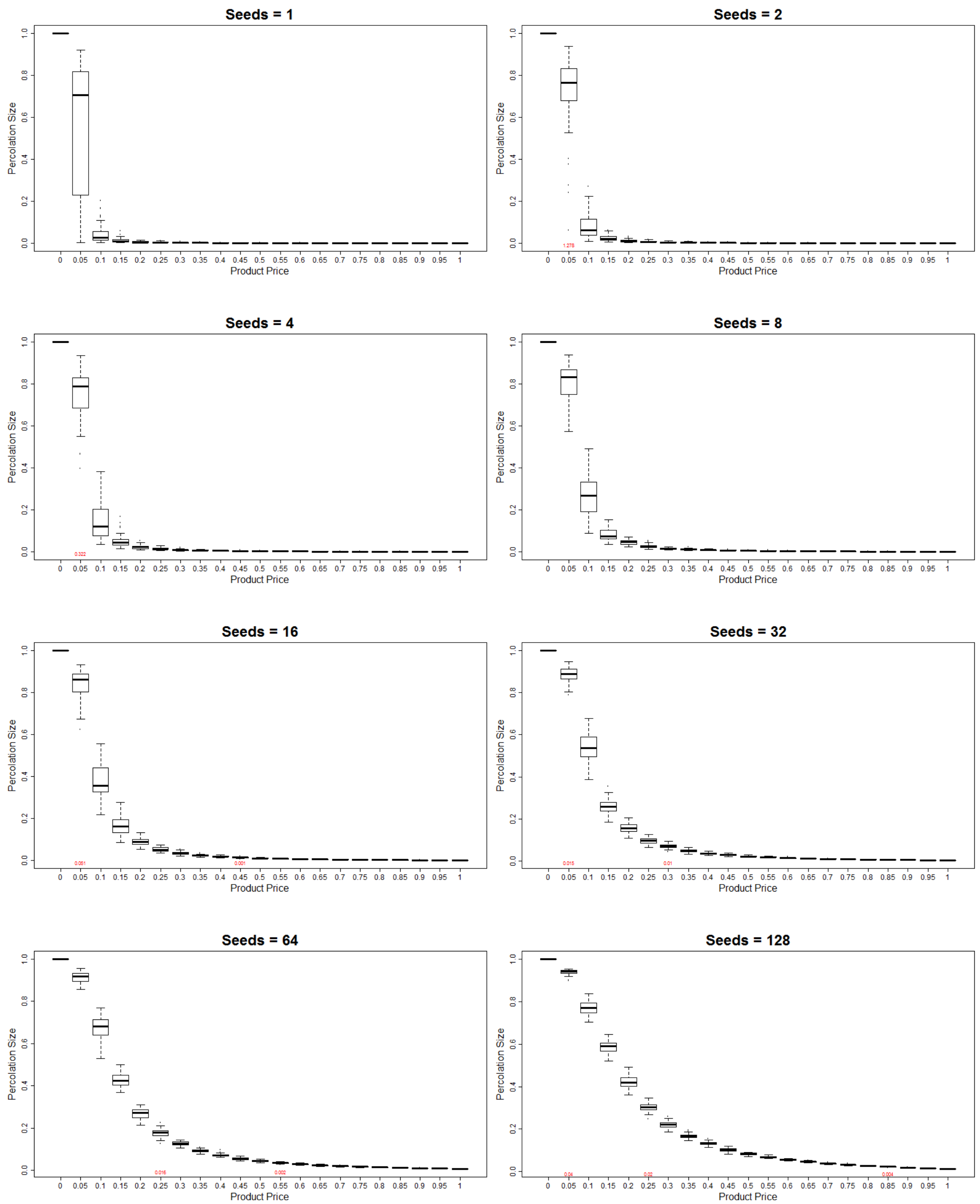
Appendix F Boxplots of seeding strategy: increasing the number of seeds (γ=0.00)

The strength of the negative outliers are, if present, shown in red just above the x-axis

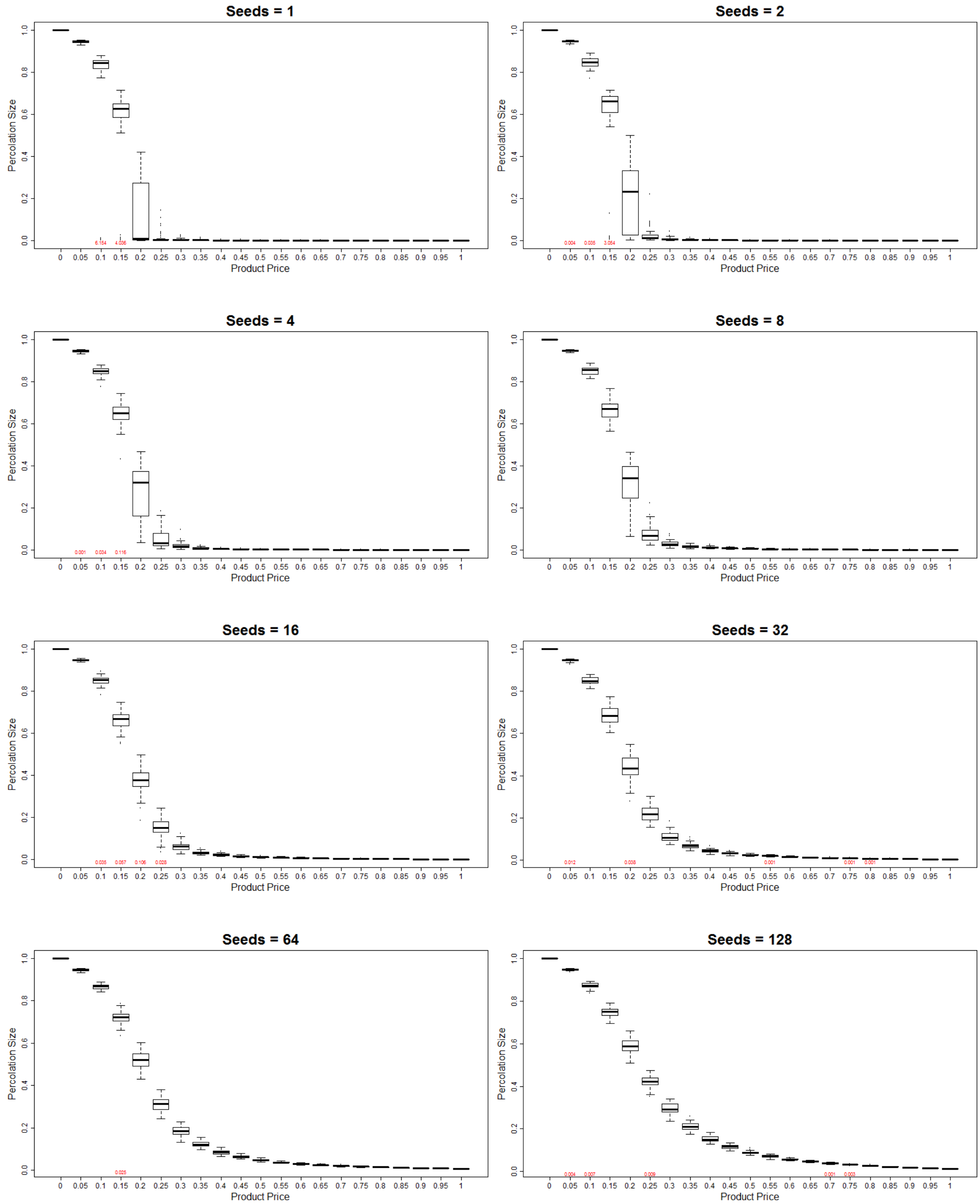
μ = 0.000



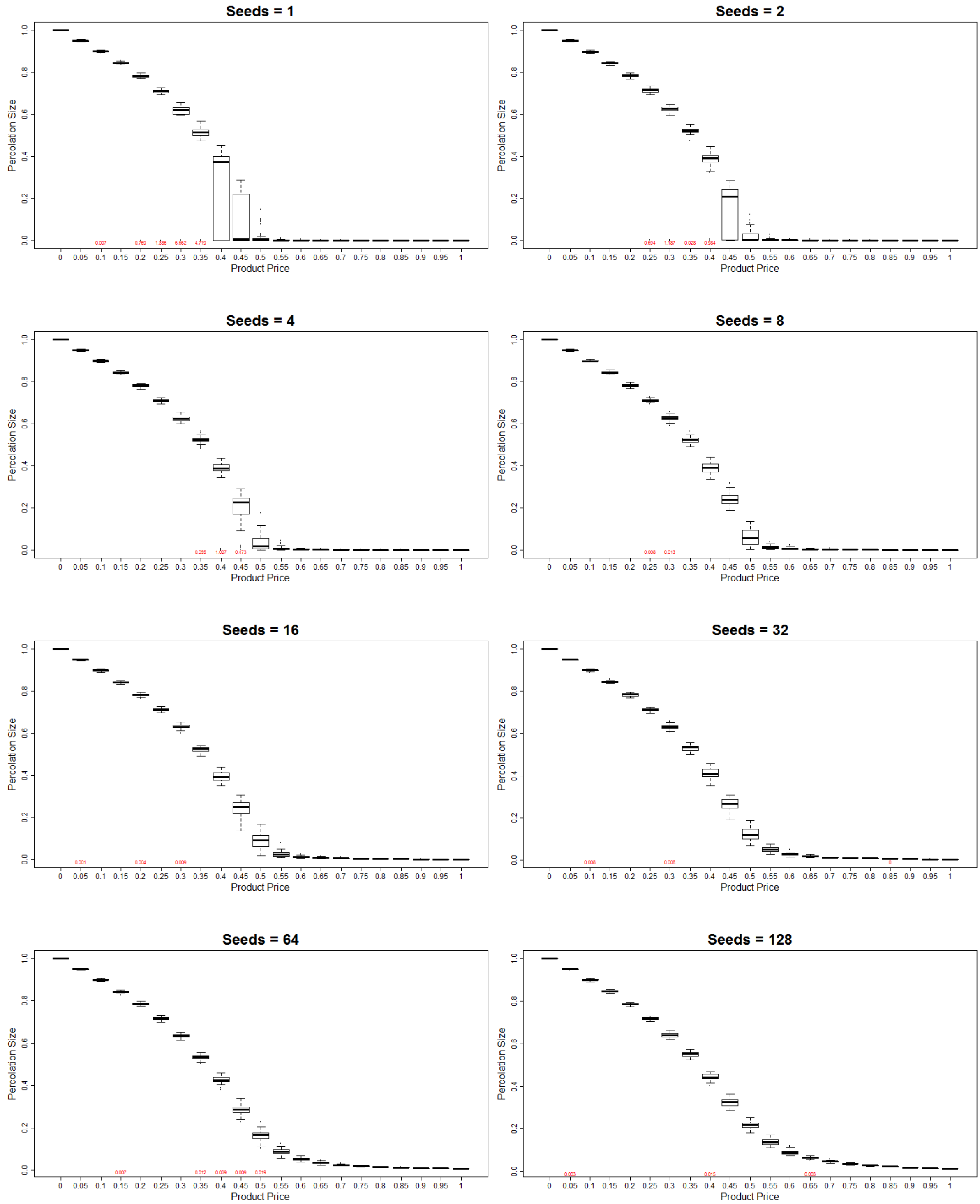
$\mu = 0.001$


Seeds = 1
Seeds = 2
Seeds = 4
Seeds = 8
Seeds = 16
Seeds = 32
Seeds = 64
Seeds = 128
Percolation Size
Product Price

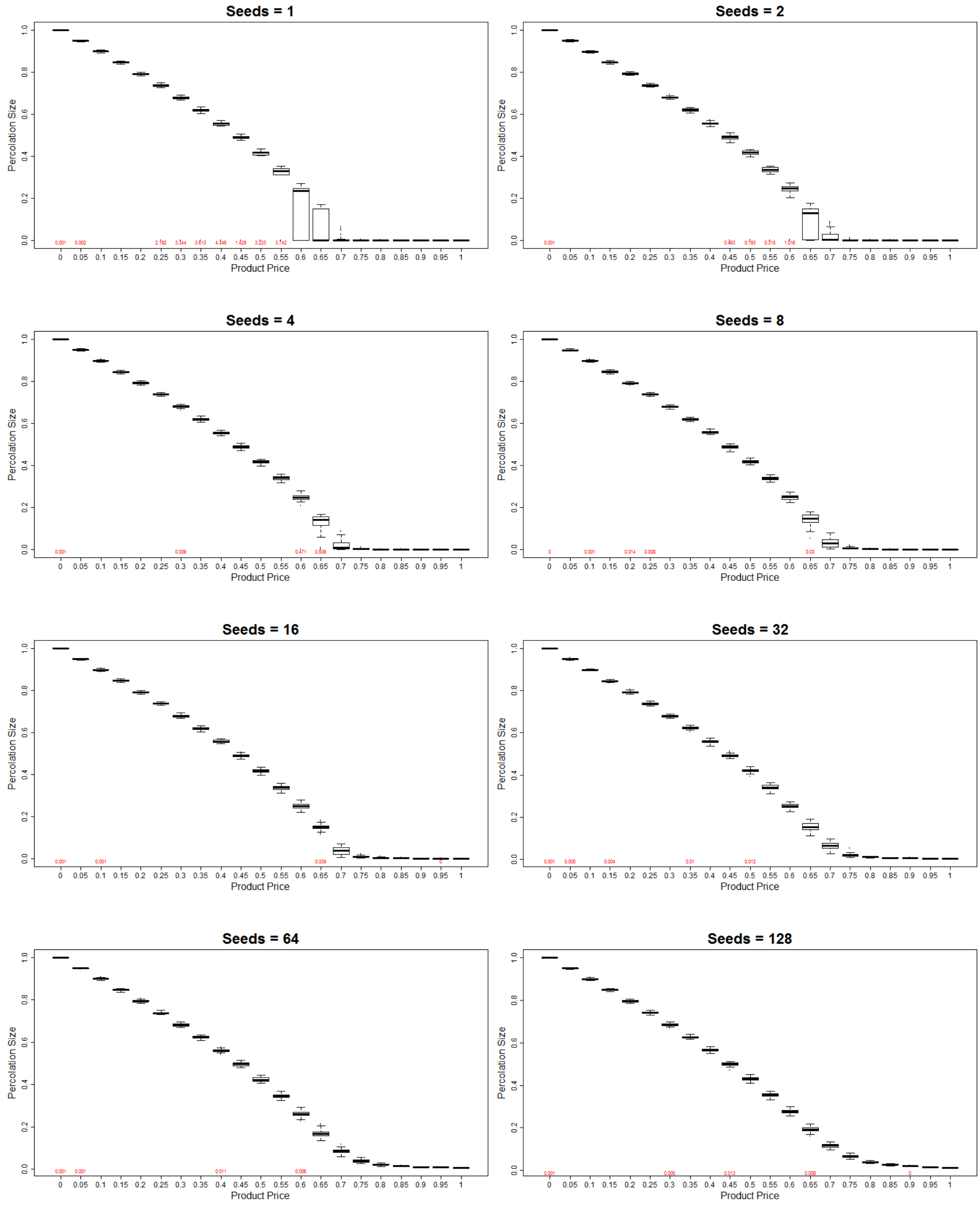
μ = 0.010


Seeds = 1
Seeds = 2
Seeds = 4
Seeds = 8
Seeds = 16
Seeds = 32
Seeds = 64
Seeds = 128
Percolation Size
Product Price

μ = 0.100


Seeds = 1
Seeds = 2
Seeds = 4
Seeds = 8
Seeds = 16
Seeds = 32
Seeds = 64
Seeds = 128
Percolation Size
Product Price
0 0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95 1
0.0 0.2 0.4 0.6 0.8 1.0

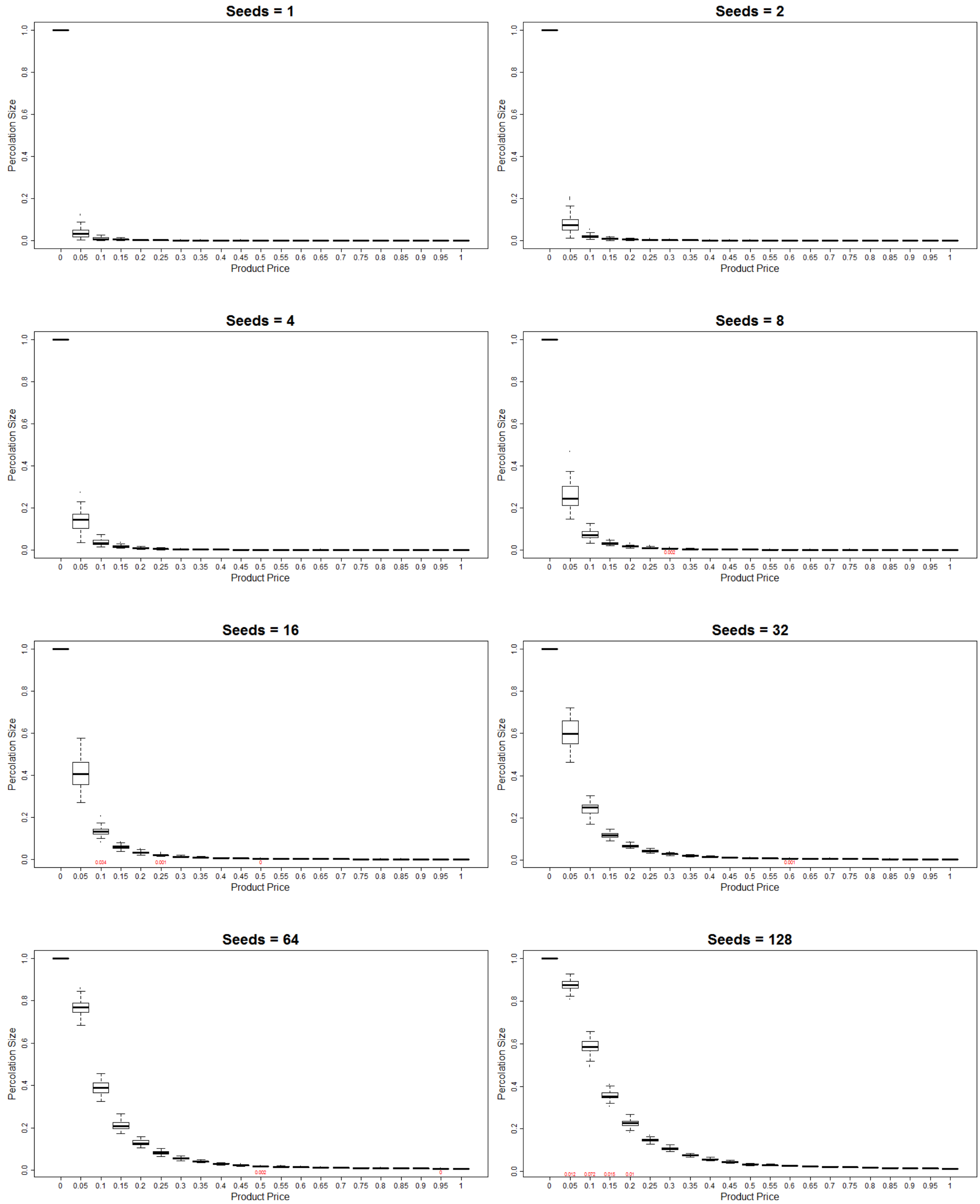
μ = 1.000


Seeds = 1
Seeds = 2
Seeds = 4
Seeds = 8
Seeds = 16
Seeds = 32
Seeds = 64
Seeds = 128
Percolation Size
Product Price
0 0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95 1
0.0 0.2 0.4 0.6 0.8 1.0

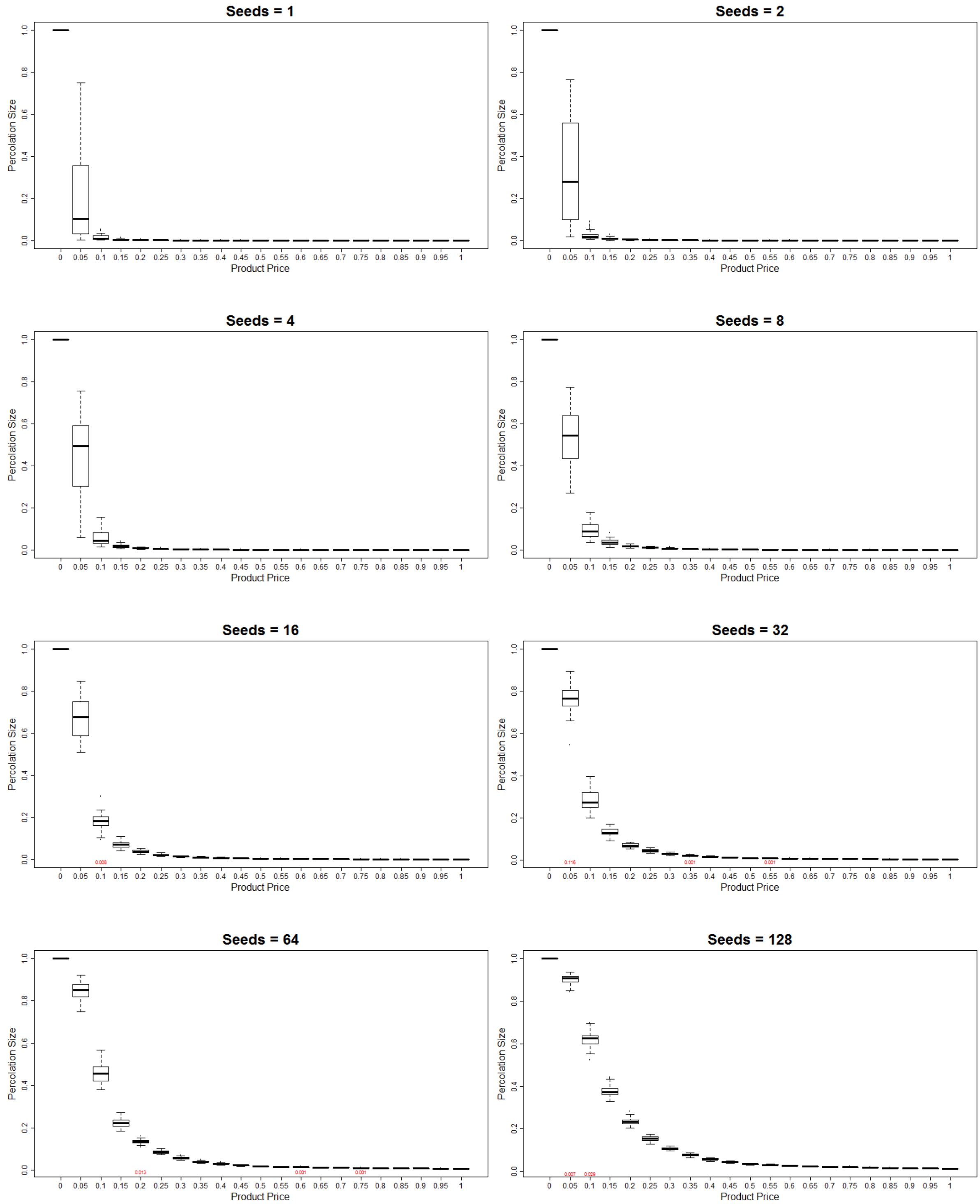
Appendix G Boxplots of seeding strategy: increasing the number of seeds (γ=1.00)

The strength of the negative outliers are, if present, shown in red just above the x-axis

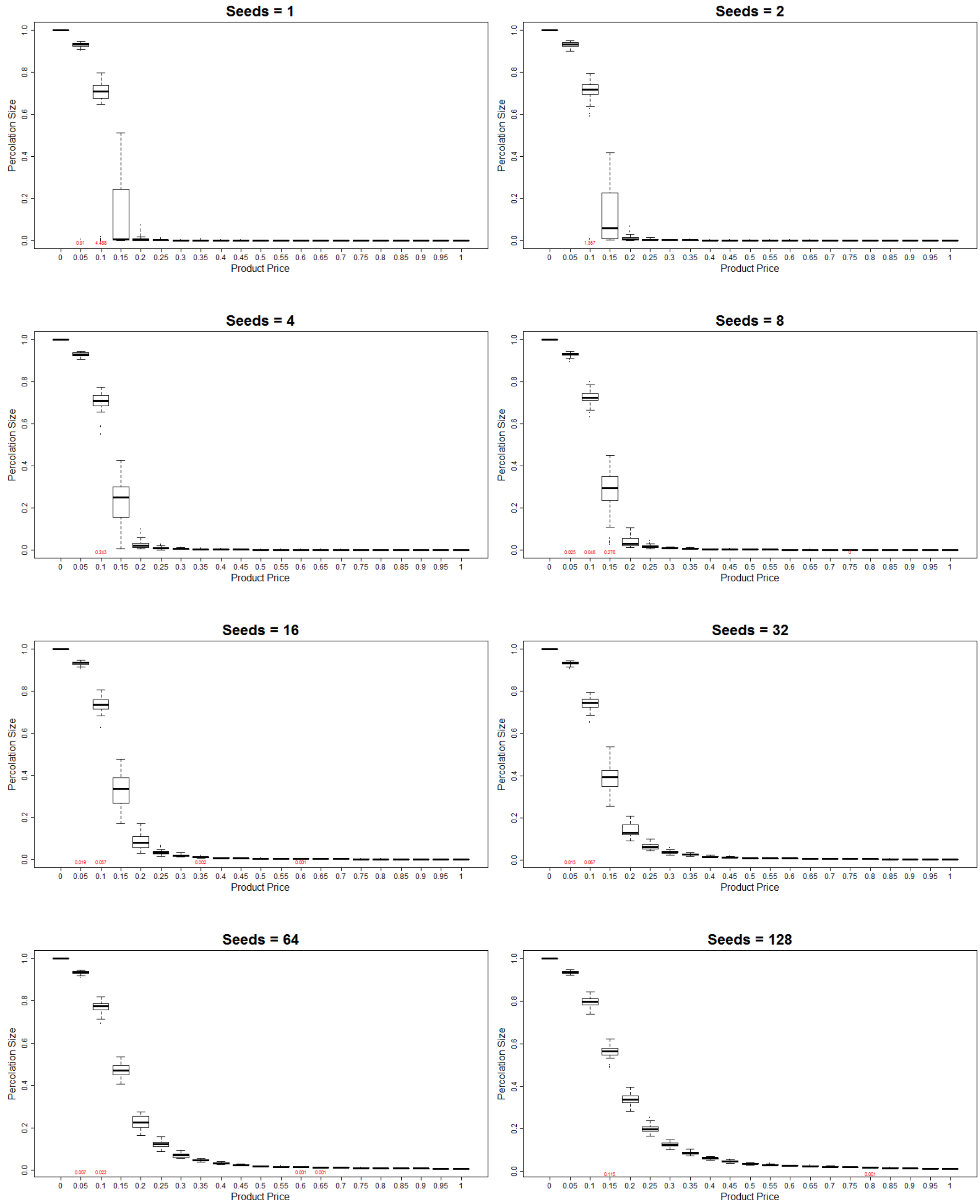
$\mu = 0.000$



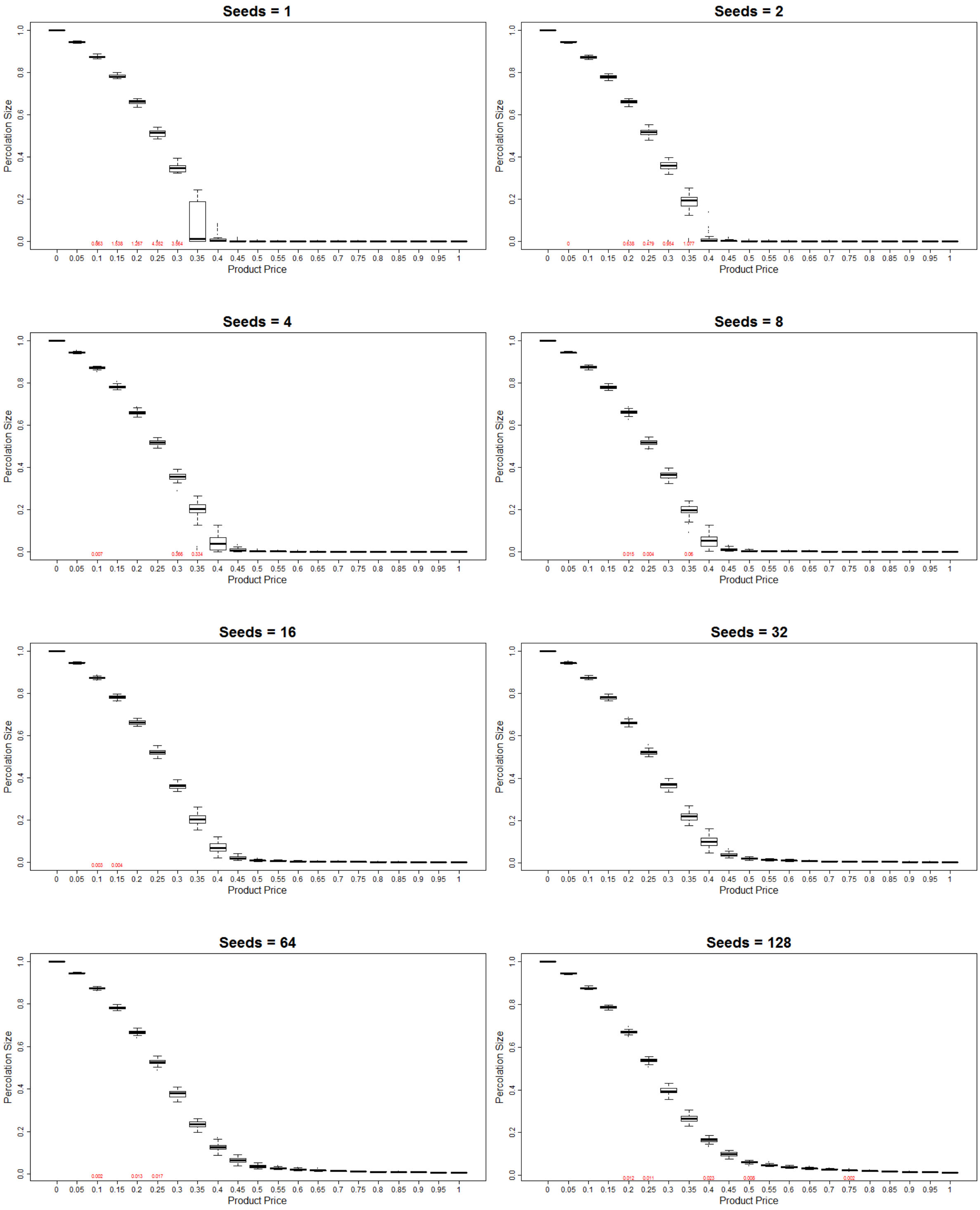
μ = 0.001


Seeds = 1
Seeds = 2
Seeds = 4
Seeds = 8
Seeds = 16
Seeds = 32
Seeds = 64
Seeds = 128
Percolation Size
Product Price

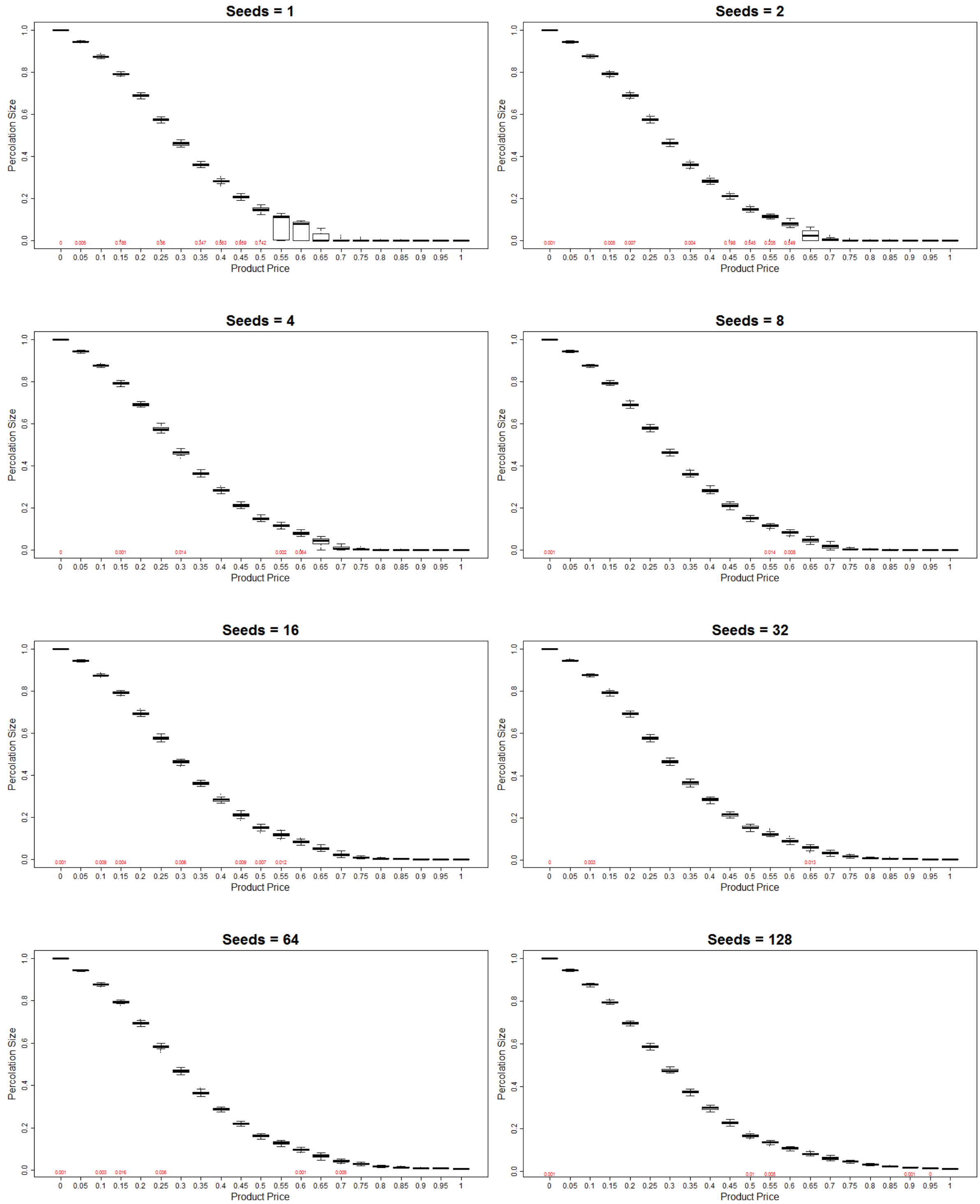
μ = 0.010


Seeds = 1
Seeds = 2
Seeds = 4
Seeds = 8
Seeds = 16
Seeds = 32
Seeds = 64
Seeds = 128
Percolation Size
Product Price

$\mu = 0.100$

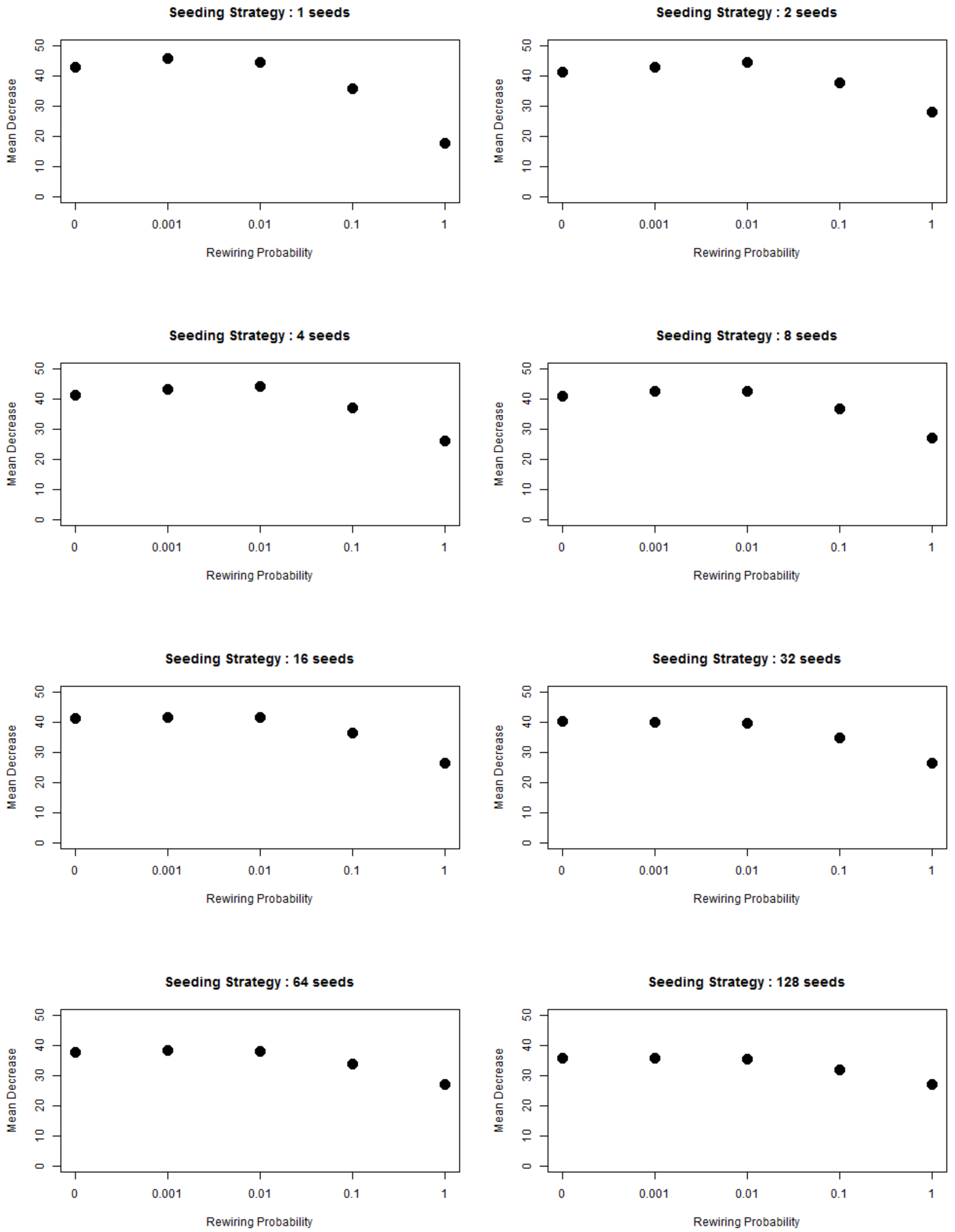

Seeds = 1
Seeds = 2
Seeds = 4
Seeds = 8
Seeds = 16
Seeds = 32
Seeds = 64
Seeds = 128
Percolation Size
Product Price
0.0 0.2 0.4 0.6 0.8 1.0
0 0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95 1

μ = 1.000



Seeds = 1
Seeds = 2
Seeds = 4
Seeds = 8
Seeds = 16
Seeds = 32
Seeds = 64
Seeds = 128
Percolation Size
Product Price
0 0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95 1
0.0 0.2 0.4 0.6 0.8 1.0

Appendix H Details of Figure 15



The mean relative decrease of percolation size, calculated as in chapter 4.1. Figure 10 and Figure 9

Appendix I Protection of seeds against NWOM

In this experiment it is explained how seeds provide protection against NWOM and how seeds that are located close to each other provide less protection. This experiment is initialized by selecting four seeds on a regular one dimensional ring lattice where agents have a degree of four. These seeds are separated increasingly with susceptible agents: for value 1, the four seeds are located next to each other. For value 2, the seeds are separated with one susceptible agent. For value 3, the seeds are separated with two susceptible agents, and so on.

When awareness propagates both from adopters and rejecters, meaning the percolation size remains equal such that only the protection of NWOM is observed, we observe in Figure 33 that the effect of NWOM is the highest for a high clustering of seeds (the mean value of 50 simulations). This decreases up to a point where the NWOM effect remains stable.

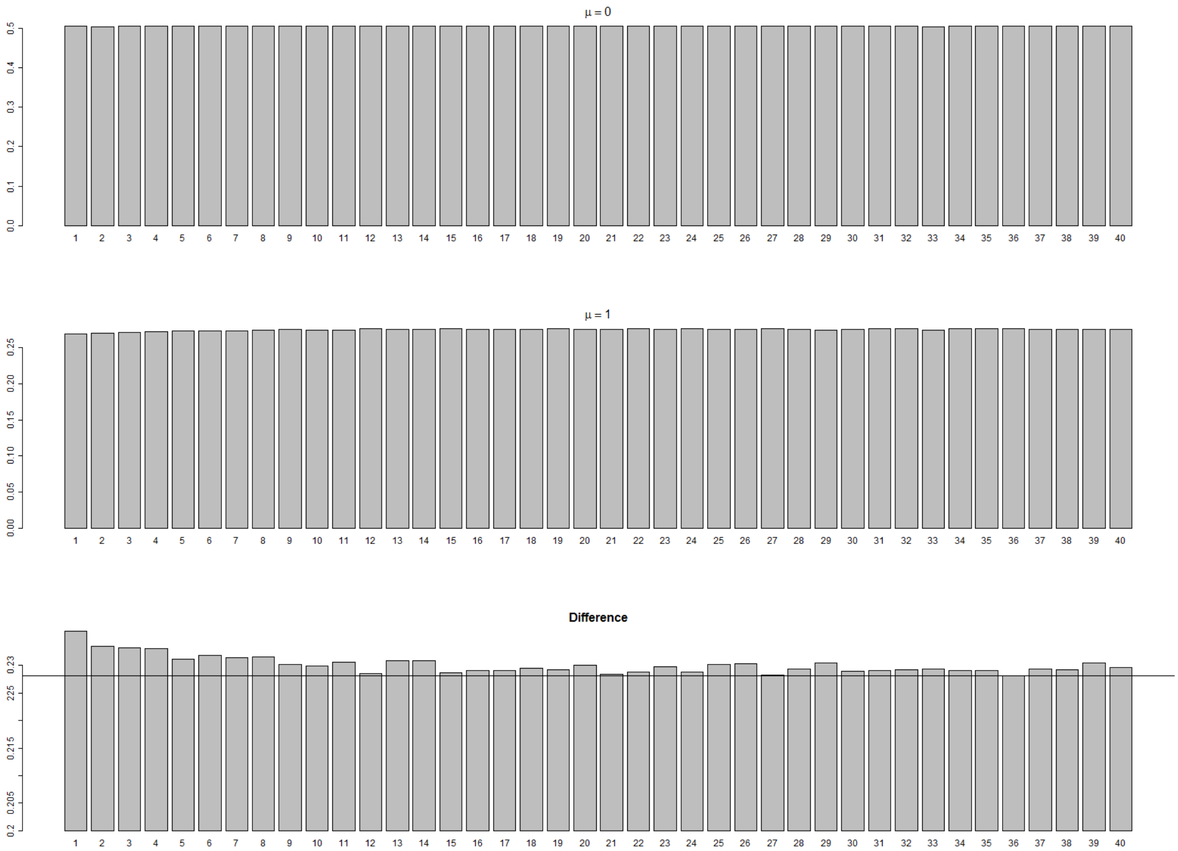
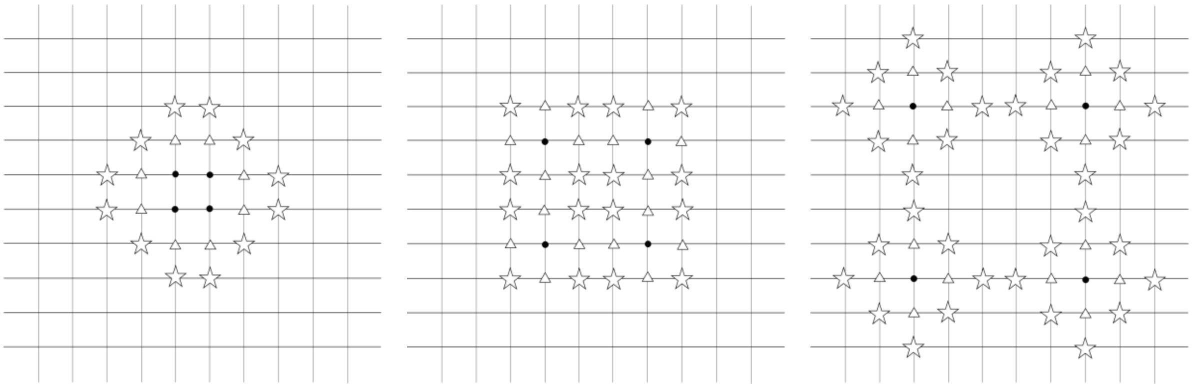


Figure 33 Protection from NWOM[20].

<u>Top:</u> Mean percolation with decreasing clustering of nodes for γ=0.00. <u>Middle:</u> Mean percolation with decreasing clustering of nodes for γ=1.00. <u>Bottom:</u> Difference between mean percolation size for γ=0.00 and γ=1.00, describing the strength of NWOM.

[20] 500 nodes. Four seeds. Percolation on ring lattice with degree = 4. Propagation for NWOM and PWOM

This can be explained because seeds can ‘protect’ susceptibles from NWOM. The most obvious example of this protection can be seen for the first neighbors of the seeds (triangles Figure 34). Since NWOM is a result of rejecting neighbors, the first neighbors of the seeds have no rejecting neighbors as these are all seeds (adopters). The second neighbors (stars Figure 34) are under the influence of NWOM from the first neighbors, but the NWOM is based upon the reservation prices of the first neighbors, and not on the adjusted reservation prices of the first neighbors since they did not experience NWOM. The further the susceptibles are away from the seeds, the less protection they have. Since the seeds in Figure 34 A and B have common neighbors, the number of protected agents is limited. In Figure 34 C the number of protected first and second neighbors is at its maximum which will remain equal when the seeds move further apart (given that the grid increases as well). This stabilizing behavior is observed in Figure 33 as well.



A. 1st neighbors: 8, 2nd neighbors: 12 *B. 1st neighbors: 16, 2nd neighbors: 16* *C. 1st neighbors: 16, 2nd neighbors: 32*

Figure 34 Positions of seeds and protection of susceptibles.

Triangles: first neighbors. Stars: second neighbors

The Effect of Negative Word-of-Mouth on Innovation Diffusion and the Performance of Marketing Strategies: an Agent Based Percolation Model

D.A. Edelkoort

Hand in date: 9th of September 2016

Master Innovation Sciences

Utrecht University – Faculty of Geosciences