Oscillatory Patterns in the Amount of Demand for Dental Visits: An Agent Based Modeling Approach

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Abstract: There are some empirical evidences indicating that there is a collective complex oscillatory pattern in the amount of demand for dental visit at society level. In order to find the source of the complex cyclic behavior, we develop an agent-based model of collective behavior of routine dental check-ups in a social network. Simulation results show that demand for routine dental check-ups can follow an oscillatory pattern and the pattern's characteristics are highly dependent upon the structure of the social network of potential patients, the population, and the number of effective contacts between individuals. Such a cyclic pattern has public health consequences for patients and economic consequences for providers. The amplitude of oscillations was analyzed under different scenarios and for different network topologies. This allows us to postulate a simulation-based theory for the likelihood observing and the magnitude of a cyclic demand. Results show in case of random networks, as the number of contacts increases, the oscillatory pattern reaches its maximum intensity, for any population size. In case of ringing lattice networks, the amplitude of oscillations reduces considerably, when compared to random networks, and the oscillation intensity is strongly dependent on population. The results for small world networks is a combination of random and ring lattice networks. In addition, the simulation results are compared to empirical data from Google Trends for oral health related search queries in different United States cities. The empirical data indicates an oscillatory behavior for the level of attention to dental and oral health care issues. Furthermore, the oscillation amplitude is correlated with town's population. The data fits the case of random networks when the number of effective contacts is about 4-5 for each person. These results suggest that our model can be used for a fraction of people deeply involved in Internet activities like Web-based social networks and Google search.

Keywords: Dental Health Care, Dental Routine Visit, Oscillatory Patterns, Agent Based Modeling, Google Trends

Introduction

1.1 Periodic health check-ups are critical in public health and provide an effective preventive measure that can mitigate chronic illnesses through early detection. With routine check-ups, early stages treatments can promote health and quality of life effectively; although, most people do not comply with such recommended check-ups. One obvious example is dental check-up.

1.2 Routine dental visits are critical for dental health promotion. Epidemiologic evidence shows that people who have regular dental visits have better oral health conditions than others (Catteau et al. 2012; Hawley et al. 1997; Catteau et al. 2014; Sheiham et al. 1985). The effects of routine dental visit on reducing level of dental caries is well known (Vehkalahti & Paunio 1988). For example, a cohort study in New Zealand reported that people who

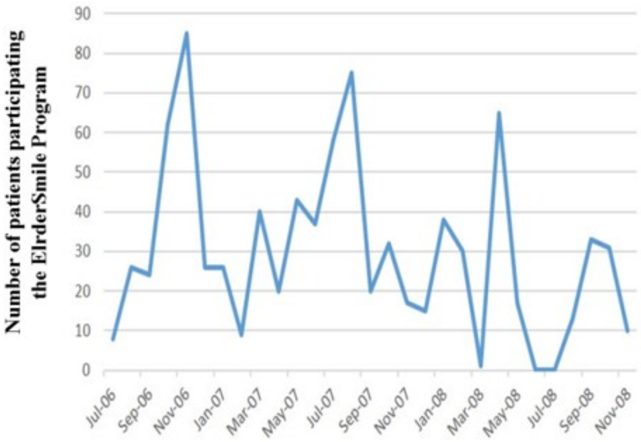

Figure 1: Oscillatory behavior of participants in the dental routine visit of the ElderSmile preventive screening program (Marshall et al. 2009; Metcalf et al. 2013).

do not maintain regular visits have three times higher levels of dental caries (Gilbert et al. 1997). It was demonstrated in a UK study that, self-reported quality of life was considerably higher for people who regularly go for routine dental visits (Mc Grath & Bedi 2001). Positive effects of routine dental care have also been observed in health care behaviors such as tooth brushing (Casanova-Rosado et al. 2014) as well as in general health literacy (Wiener & Shockey 2014). Although proper frequency of routine dental visits can be different for different individuals and societies, on average, presumably six months period may be the optimal interval between two successive visits as advised by most dentists (Frame et al. 2000).

1.3 Since promoting routine dental visit is an important concern for health practitioners, understanding factors that promote such visits is crucial. Previous studies have shown that lack of compliance with routine dental visits may be rooted in economic reasons (Peltzer & Pengpid 2014), stress and anxieties associated with visiting dentists (Sohn & Ismail 2005), oral health knowledge (Wiener & Shockey 2014) and perceived oral health status (Sohn & Ismail 2005). Although there is a rich literature investigating individual factors, no study has examined how these individual level factors can influence public behavior in aggregate.

1.4 Many examples exist on how individuals can influence each other's health seeking behavior. Family members can have an impact. If parents start teaching their toddlers to brush their teeth in early ages, their other health-related preventative activities can influence their children's long term healthy behavior and improve their routine habits. Similarly, friends and colleagues can influence healthy behaviors. Such social influences in aggregate can lead to counter-intuitive emerging behaviors, i.e., a characteristic of complex social systems.

1.5 A series of recent studies by Metcalf et al. (2013) showed that dental visits, in aggregate, can follow wild oscillatory patterns. Specifically, they showed that dental visit promotion programs in New York (the ElderSmile program) have been going through cyclic patterns of demand. They argued that the oscillatory high level aggregate patterns were complex behaviors and thus difficult to explain with linear regression models (Marshall et al. 2009; Metcalf et al. 2013). Figure 1 shows the observations from the ElderSmile preventive screening program in New York City by the Columbia University College of Dental Medicine during July-2006 to November-2008 (Metcalf et al. 2013). This program operated in North Manhattan (in which the elderly population have many friendship connections with their neighbors) and the trend of the participating population showed an oscillatory behavior with an average period of about 8 months. It should be noted that the pattern is not seasonal. Therefore, it was suggested that the pattern should be described by modeling the interactions among elders through their friendship network. This interaction somehow synchronizes the friends' decision to go for the visit (Metcalf et al. 2013). It should also be mentioned that this oscillatory pattern potentially might have serious implications on resources for the screening program as well as other similar programs.

1.6 By analyzing the big data provided by Google Trends service, we find another evidence of potential complex and cyclic patterns in people's attention to dental health. Google query trends for the word "dentist" in different US towns (Figure 2) show that public attention, especially in smaller towns, has been following oscillatory patterns. As Fig. 2 demonstrates, in a sample of three small and three large US towns, public attention to dental care represented by their online behavior, follows a cyclic patterns. The highest attention (search) points for different towns happen in various months, showing the patterns are not limited to seasonal changes. The time period of these patterns are different between 4-7 months. In addition, the difference between oscillation amplitudes in

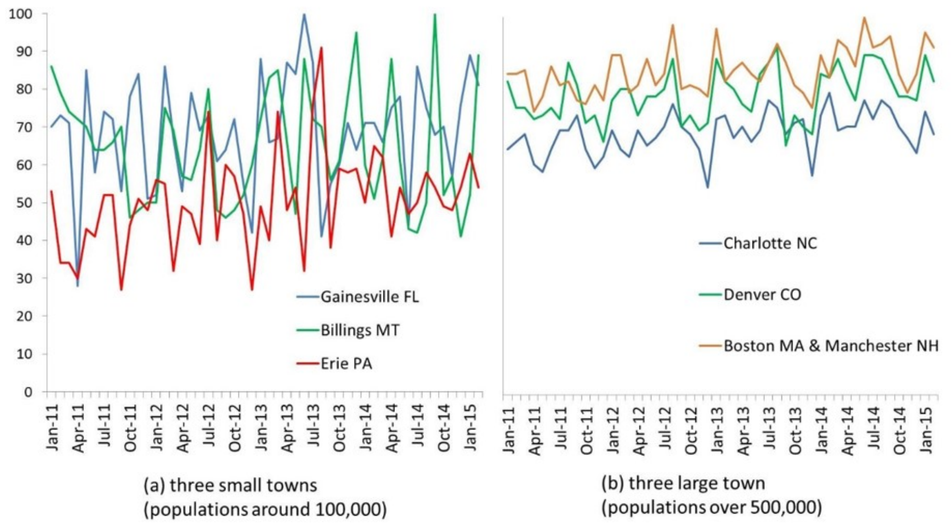

Figure 2: Trends of public attention to dental care represented by Google search queries for the word "dentist". Google search queries for (a) three relatively small and (b) three relatively large US cities. The maximum value of queries is represented by 100 and other values are respective percentages of the maximum. Note: The public attention patterns to the word "dentist" show oscillatory behaviors. The amplitude of oscillation is larger in smaller towns.

small and large cities suggests that these patterns can be originated from a "Word Of Mouth" process in which people attract each other's attention to oral health. The different patterns in the small and large cities can be regarded to the different social network properties. In small towns, the distance between people in the social network is smaller than those in large cities which helps a faster "Word Of Mouth" process in the society. Regarding the search for the "dentist" as a sign of public attention to dental visits, it also suggests that these oscillations may have the same source as the cyclic behaviors in the number of dental visits (like Figure 1).

1.7 Considering the importance of understanding collective dental care behaviors as a social phenomenon, we raise a question: can simple decision making rules at individual level result in oscillatory demand for routine visits? In order to answer this question, from a methodological perspective, by taking a dynamic modeling approach, we develop an agent-based model that aims to model individuals' routine dental check-ups behavior. Our approach offers another example of how dynamic modeling can be used to study complex patterns especially in public health arena (Auchincloss & Roux 2008; Brookmeyer et al. 2014; Day et al. 2013; Gorman et al. 2006; Laskowski et al. 2011; Leischow & Milstein 2006). The model proposes a "Word Of Mouth" process in which people promote each other to go for dental visit through social networks.

1.8 Based on a simulation model, this paper postulates that: 1) given simple rules about how individuals (agents) go to dentists and also interact through social networks, it is likely to observe oscillatory patterns in the societal level. 2) Such a cyclic pattern is a function of social network characteristics that connects patients to each other. Our theory does not aim at explaining all reasons for routine dental visits (or any other routine medical visits), and does not aim at rejecting any previously stated reason for how individuals seek healthcare. However, it provides a novel "endogenous" theory of demand for routine dental visits, a theory that focuses on social dynamics of a preventive healthy behavior. 3) Finally, focusing on the fraction of people involved in web based activities, we compare the model results to an empirical data from Google Trends. This comparison demonstrates the oscillatory pattern of public attentions to oral and dental health issues, as well as the importance of routine visits that, can be predicted by the proposed model. In addition it indicates that the model is able to successfully explain the population dependency of these patterns for different US towns (Figure 2).

Modeling

2.1 In order to reproduce the observed oscillatory pattern of dental visit demand, here an agent-based model is proposed. As previously mentioned in the introduction section, the cyclic pattern has specific properties: it is population dependent (Figure 2) and the period of the oscillations is about a few months. To reproduce these properties, the model is built based on a "Word Of Mouth" process, where agents interact through specific social

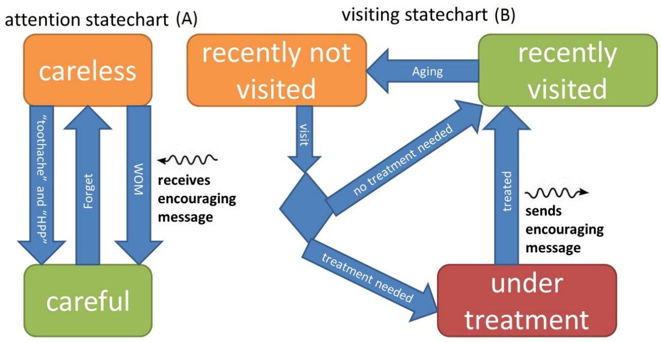

Figure 3: Statecharts of the agent-based model. The statechart on the left (A) indicates the level of patient's attention to the necessity of routine visit and the statechart on the right (B) shows the visiting state. HPP stands for health promotion programs, and WOM stands for word of mouth.

networks. In addition, to simulate the cyclic behavior with a period of few months, we should also consider a delay of almost the same time period in which the simulation almost returns to its initial condition. Fortunately, there is a definite dental clinical delay for this time period which is related to necessary time intervals between routine dental visits advised by dentists. The visiting interval of about six months is assumed to be the effective interval for which the dental health status might become at risk (Frame et al. 2000).

2.2 The basic structure of the proposed model is as follows: In each time period, some people (agents) go to dentist. The decision to visit a dentist is influenced by individuals' state of attention to dental health (being careless or careful about their dental health), and whether or not they have recently (within the last six months) visited a dentist. When someone visits a dentist in order to do a check-up, it is possible that, he/she goes under treatment. It is assumed that people who have recently been under treatment encourage others to visit a dentist.

2.3 We run the model for different population sizes, network structures, and contact ratios as described in the model parameters section.

2.4 For coding and simulation purposes, AnyLogic software is used. In the following, we describe detailed formulation and coding of decision rules and network structures of the model. The model code can be found at: `https://www.openabm.org/model/4927/version/1/view`.

Decision rules

2.5 Figure 3 depicts a flowchart (statechart) of an agent's decision making model. In each time period, two statecharts will indicate each agent's status. First is the state of attention about dental care (statechart A) which includes two conditions: *careful* (CF) and *careless* (CL). Second statechart indicates the agents visiting state (statechart B) where in each time period, each patient is in one of the states of *recently visited* (RV), *recently not visited* (RNV) and under treatment (UT). Thus for any agent i and time t we have:

$$A_{i,t} \in \{CF, CL\} \tag{1}$$

$$B_{i,t} \in \{RV, RNV, UT\} \tag{2}$$

where $A_{i,t}$ and $B_{i,t}$ represent states of agent i at time t regarding her level of attention to dental care and visiting state, respectively.

Transitions within attention states (statechart A)

2.6 People's attention to dental care (statechart A) can change between CL and CF. In our model, state of attention can increase (change from CL to CF) through toothache, public Health Promotion Programs (HPP), and word of mouth (WOM). The probability of transition due to toothache or HPP is represented by β. The WOM transition happens whenever the agent receives an encouraging message from her friend. Therefore, we can write:

$$P(A_{i,t} = CF | A_{i,t-1} = CL) = \max(WOM_{i,t}, \beta) \tag{3}$$

where $WOM_{i,t} = 1$ if agent i has received an encouraging message to seek dental care at time t, and is zero otherwise.

$$WOM_{i,t} = \begin{cases} 1, & if \quad \exists j | S_{ji,t-1} = 1 \\ 0, & Otherwise \end{cases} \tag{4}$$

where $S_{ji,t-1} = 1$ if agent j sends encouraging message to i at time $t-1$.

2.7 The level of attention deteriorates (changes from CF to CL) with a delay of *time to forget*, τ, formulated as following:

$$\tau = M\tau_N \tag{5}$$

where τ_N is the normal time to forget and M is a multiplier, which represents effects of intensity of recent treatment on reminding the necessity of dental health. The transition from CL to CF can be expressed in terms of the transition probability as follows:

$$P(A_{i,t} = CL | A_{i,t-1} = CF) = \begin{cases} 1, & if \quad T_{CF} \geq \tau \\ 0, & if \quad T_{CF} < \tau \end{cases} \tag{6}$$

where T_{CF} is the time since the agent has become *careful* in her last transition.

Transitions within visit states (statechart B)

2.8 As mentioned before, agents are categorized into three groups: *recently not visited* (*RNV*), *recently visited* (*RV*), and currently *under treatment* (*UT*). Agents in RNV state are the ones who have not visited dentist in the past six months. Agents in the RV state visited dentist at least once in the past six months. Agents in the UT stage are currently under treatment.

2.9 In the model agents' decision to visit a dentist ($V_{i,t} = 1$) follows a simple rule: An agent visits a dentist if her attention and visiting states are respectively careful ($A_{i,t-1} = CF$) and recently not visited dentist ($B_{i,t-1} = RNV$). Mathematically:

$$V_{i,t} = \begin{cases} 1, & if \quad A_{i,t-1} = CF \quad and \quad B_{i,t-1} = RNV \\ 0, & otherwise \end{cases} \tag{7}$$

2.10 The transition probabilities can be written as:

$$P(B_{i,t} = RNV | B_{i,t-1} = RV) = \begin{cases} 1, & if \quad T_{RV} \geq 6 \quad months \\ 0, & otherwise \end{cases} \tag{8a}$$

$$P(B_{i,t} = UT | B_{i,t-1} = RNV) = \begin{cases} RT, & if \quad V_{i,t} = 1 \\ 0, & otherwise \end{cases} \tag{8b}$$

$$P(B_{i,t} = RT | B_{i,t-1} = RNV) = \begin{cases} 1, & if \quad V_{i,t} = 1 \quad and \quad B_{i,t} \neq UT \\ 0, & otherwise \end{cases} \tag{8c}$$

$$P(B_{i,t} = RT | B_{i,t-1} = UT) = \begin{cases} 1, & if \quad T_{UT} \geq T_t \\ 0, & otherwise \end{cases} \tag{8d}$$

where T_{RV} and T_{UT} represent the time from when the agent's states has changed to *RV* and *UT* respectively, in her last transition. Whenever an agent visits a dentist, with some probability called *required treatment* (*RT*), she will need treatment. *Treatment time* (T_t), indicates how much time is needed to cure the agent. In addition, we have considered whenever an agent changes its state from UT to RV, she will send an encouraging message to some randomly chosen friends of her.

$$S_{ji,t} = \begin{cases} 1, & if \quad i \in RC_{m,j,t} \quad and \quad B_{i,t} = RV \quad and \quad B_{i,t-1} = UT \\ 0, & otherwise \end{cases} \tag{9}$$

in which $RC_{m,j,t}$ is a set of m randomly selected agents from the neighbors of agent j in the social network. In other words, m is the number of agent j's friends that she will encourage them after her treatment. We have varied m in our simulations to investigate the effect of word of mouth in the collective behavior.

2.11 We should emphasize that, focusing on the demand side, we have ignored the supply restrictions in our model. It should be mentioned that considering the limited supply side would probably smoothen the oscillations.

Social network structures

2.12 We used three major social network structures of *Random*, *Ring Lattice*, and *Small World* in our simulations, as described in the following.

Random network

2.13 In this structure each node (agent) is assumed to be randomly connected to a certain number of other nodes. Nodes are connected to any other one with the same probability (Figure 4). In our simulations all nodes are assumed to be randomly connected to $L = 10$ other nodes on average. This means that any agent is connected to 10 other agents as friends (on average) and encourages m number of them ($m \leq 10$) to visit a dentist. We used AnyLogic pre-defined Random network standard structure to create this network. AnyLogic uses Erdős and Rényi (ER) random graph model to create the Random structure. In this model, distribution of each node's degree is binomial. In our case, since we have large number of nodes and also the mean degree of these nodes was constant, one can show the binomial distribution to be approximately equivalent to Poison distribution (Newman 2010). In addition, in order to analyze the sensitivity of the model to the homogeneity of networks, we added (or subtracted) each node's degree by a normal variable with an average equals to 0 and variance equals to 5. This addition (or subtraction) was performed by adding (or removing) a link between the node and another random node.

Ring Lattice network

2.14 In this structure, nodes are placed on a ring and each node is connected to a definite number of its neighbors. Connections in this type of network are local and there is no long range connection within the network structure (Figure 4). In these simulations, all nodes are assumed to be connected to 10 neighbors and they send encouraging messages to m neighbors. We used AnyLogic pre-defined Ring Lattice network standard structure to create the network. The algorithm for creating a Ring Lattice network with nodes degree equal to 10 is as follows: first, a ring layout of agents is built, then we start from the first agent on the ring and connect it to its next 5 neighbors (clockwise). Repeating the process for all agents, each one will be finally connected to 10 adjacent agents, equally divided on its both sides on the ring. In order to analyze the sensitivity of the model to the homogeneity of the network structure, we then modify the network by adding (or removing) normal random number, with average 0 and variance 5, of edges to (or from) each node. In order to maintain the general structure of Ring Lattice network, when a link is removed, we choose the last connection in clockwise direction of that particular agent and when adding a link, we connect that agent to its last clockwise not connected neighbor.

Small World network

2.15 In this structure, connections are mostly local while it permits a certain fraction of connections to be long ranged. To be more specific, this network is based upon Ring Lattice network where each node is connected to a certain number of its neighbors. Then a given percent of local connections are replaced by connections between randomly chosen nodes with no limitation on their distance. Therefore, a Small World network structure can be considered as a combination of Ring Lattice and Random network (Figure 4). We used the pre-defined Small World network in AnyLogic assuming 10 connections for each agent and 5 percent of the connections to be random ($\kappa = 0.05$). For creating this structure, AnyLogic follows Watts–Strogatz mechanism (Watts & Strogatz 1998). According to this mechanism, first Ring Lattice network should be created with a constant degree of each node as described before. Then for each node i an edge (n_i, n_j) $(i < j)$ is selected with probability κ and it is rewired with (n_i, n_k) where κ is chosen uniformly at random. In order to analyze the sensitivity of the model to the homogeneity of the network structure, we then added (or removed) a normal random number, with an average of 0 and a variance of 5, of edges to (or from) each node.

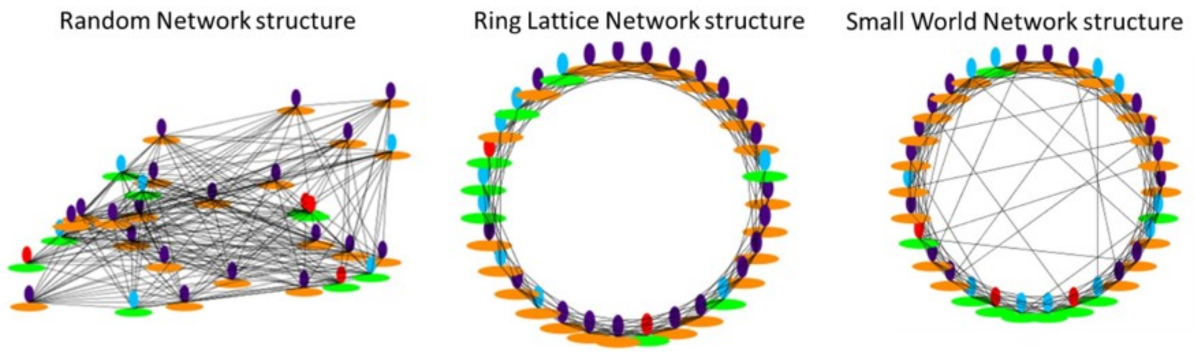

Figure 4: Schematic of different types of network structures. Agents with orange and green body (the lower oval) are careless and careful respectively. Agents with purple, blue and red head (the upper oval) are RNV, RV and UT, respectively.

Parameter	**Description**	**Value**
Visit Time (T_0)	Proper period between successive routine visits.	6 months
Toothache & HPP Rate (β)	Probability of a *careless* person become *careful* by toothache or public advertisement.	0.025
Contacts After Treatment (m)	Number of people who are encouraged to visit a dentist by a person who has recently been treated.	Varied between 0 to 10
Forget Time (τ_N)	Normal time for a careful person to forget and become *careless*.	Normal random variable with average of 1 month and variance of 0.5 month
Treatment Forget Multiplier (M)	Forget Time is multiplied by this value when the person has been recently treated.	3
Treatment Requirement Probability (RT)	The probability of requiring a treatment during a visit.	0.5
Treatment Time (T_t)	Duration of treatment.	Normal random variable with average of 0.5 month and variance of 0.25 month
Total Population (N)	Total population	Varied 100 - 20000
Connection Number (L)	Average number of connections of each individual	10 people
Small World Network Parameter (κ)	Fraction of non-local connections in the Small World network.	0.05

Table 1: Short description of the ABM model parameters and their values.

Model parameters

2.16 In total, we have simulated 115,000 experiments which comprise 3 network structures, 11 different values of contacts after treatment (0-10), 7 different populations (100, 200, 500, 1000, 2000, 5000 and 20000), and 500 different random seeds. All models were simulated for the time period of 500 months and simulation time step is one-tenth of a month (0.1 month). All other parameters and their values are presented in Table 1.

Oscillation measure

2.17 In order to assess the intensity of oscillations in the simulations, we focus on the number of *careful* people. This variable has a continuous behavior over time and other variables like the number of visits over time almost imitates the same pattern. In addition, as we will see in the following sections, this variable is used to fit the empirical data.

2.18 The spectral density P of the trends can be used as a measure to examine how much the patterns of the results are oscillatory (Bloomfield 2004), as in the following:

$$P(f) = |FT\{x(t)\}|^2 \tag{10}$$

where P is the spectral density, f is the frequency and $FTx(t)$ is the Fourier Transform of the continuous time series $x(t)$ (here the trends of number of careful people).

2.19 In order to have a better measure for the magnitude of oscillations, in a specific frequency interval, we use the normalized spectral density integral (NI) defined as follows:

$$I = \int_{f_1}^{f_2} (P(f) - P_0(f))\,\mathrm{d}f \tag{11a}$$

$$I_0 = \int_{0}^{f_{max}} P(f)\,\mathrm{d}f \tag{11b}$$

$$NI = \frac{I}{I_0} \tag{11c}$$

where I is the spectral density integral between f_1 and f_2 (the frequency interval of interest), I_0 is the total spectral density integral and NI is the normalized spectral density integral. $P_0(f)$ indicates the condition in which no agent sends encouraging message ($m = 0$). This small value is subtracted from $P(f)$ so that we just integrate, in the interval f_1 and f_2, over the spectral density relevant to WOM and we exclude the effect of the random process due to toothache and HPP.

2.20 Considering the lower and upper bound for the frequency interval of interest to be $f_1 = 0.1$ (1/Month) and $f_2 = 0.2$ (1/Month) we can calculate NI. This frequency range is relevant to oscillations period times from 5 to 10 months which contains the 6 months regular dental visiting intervals.

Results

Random network

3.1 The simulation results for population 500 and m equals to 4 and 10 for Random structure are shown in Figure 5. This figure clearly shows an oscillatory pattern and the oscillation intensity grows as the number of contacts after treatment increases. The period of the oscillations is almost 7-8 months.

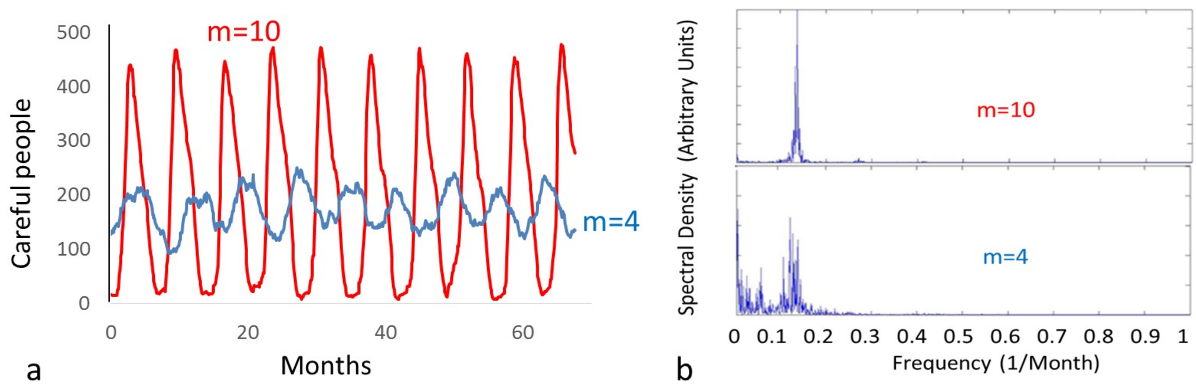

Figure 5: Time series and the relevant spectral densities of the trends of careful people in Random network simulations. Simulation results for a Random network with populations $m = 4, 10$ and population $N = 500$. Note: a) Time series, (b) Spectral densities

3.2 The simulation results for the value of *NI* in the Random network for different populations are shown in Figure 6a. For $m = 0$, there is no collective oscillation and by increasing m, oscillations gradually appear especially

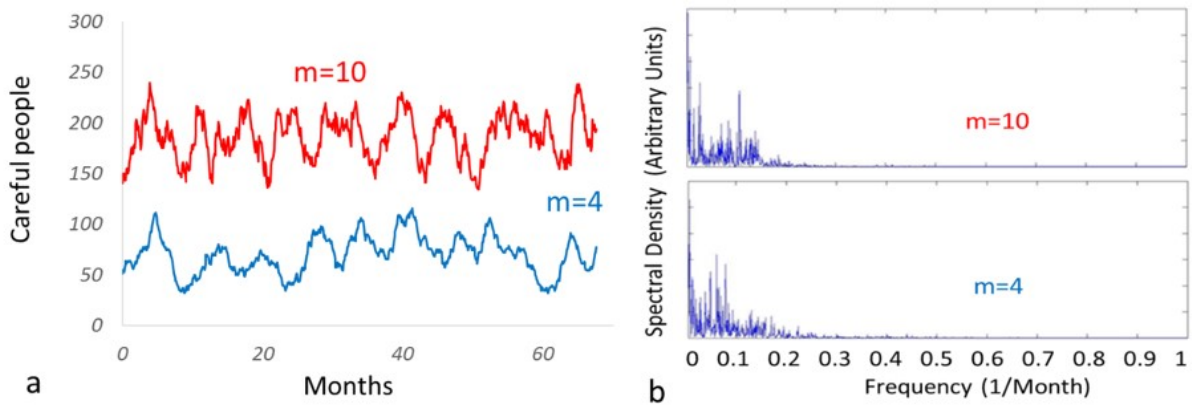

Figure 7: Time series and the relevant spectral densities of the trends of careful people in Ring Lattice network simulations. Simulation results for a Ring Lattice network with populations m=4, 10 and population N=500. (a) Time series, (b) Spectral densities

for small populations. For different populations all graphs asymptotically tend to 0.4. We will show in the next section that this is almost the maximum value of the normalized spectral density integral NI_{max} 0.4.

3.3 Furthermore, the dependency of the oscillation intensity on the population is also illustrated in Figure 6b. This figure indicates that the simulation results are almost linear in a log-log diagram. We have also fitted the results for different values of "Contacts After Treatment" to a linear relation. These relations will be used in the following sections to compare the simulation results to empirical data. Interestingly, this figure illustrates that the results are independent of population size for larger values of *m*.

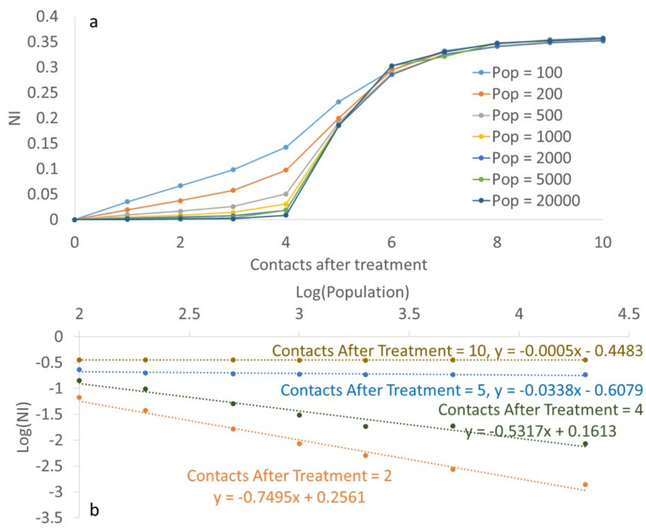

Figure 6: Simulation results for Random network structure. (a) Normalized spectral density for different "Contacts After Treatment", (b) log-log diagram showing the dependency of NI to population.

Ring Lattice network

3.4 The simulation results for NI in Ring Lattice network is illustrated in Figure 8a. According to this figure and by comparing it with Figure 6a, it can be seen that NI values are much smaller than those for Random network. In addition, in contrast to Random network, the dependency of the oscillatory pattern on population, for larger values of m, is clearly observable (Figure 8b).

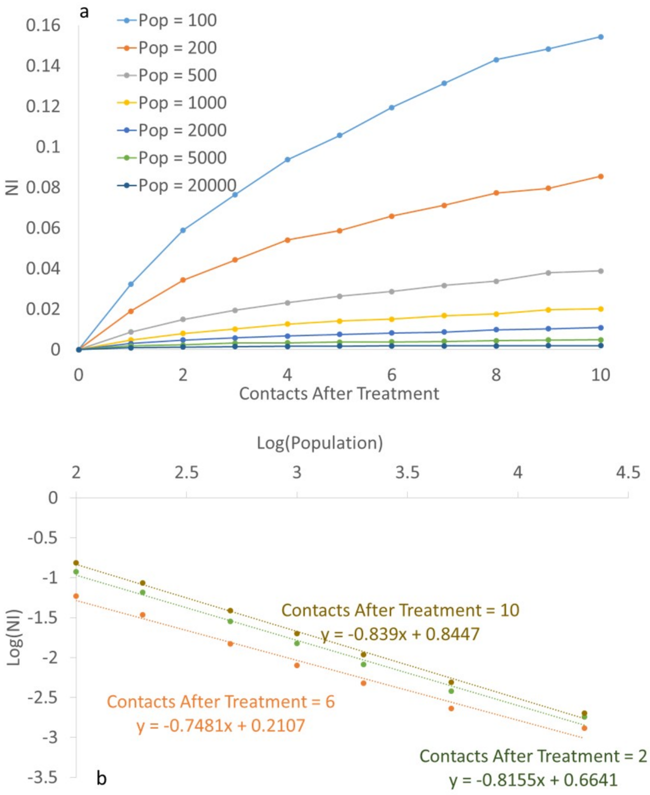

Figure 8: Simulation results for Ring Lattice. (a) Normalized spectral density for different "Contacts After Treatment", (b) log-log diagram showing the dependency of NI to population.

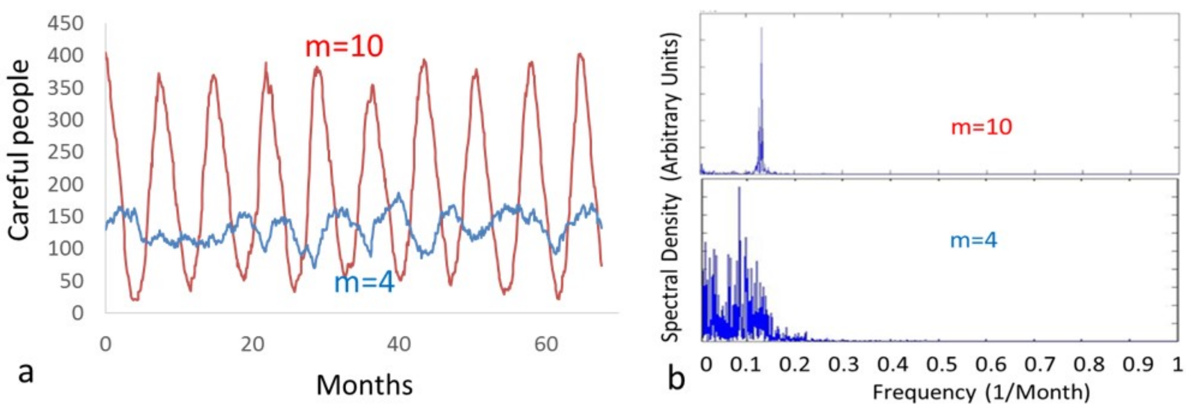

Figure 9: Time series and the relevant spectral densities of the trends of careful people in Small World simulations. Simulation results for a Small World network with populations m=4, 10 and population N=500. (a) Time series, (b) Spectral densities

Small world network

3.5 The simulation results for population 500 and m equals to 4 and 10 for Small World structure is shown in Figure 9. In terms of pattern of connections, the Small World network is structurally between Random and Ring Lattice network structures. Therefore, it is expected that the speed of sending encouraging messages is in between those two extremes. This can be observed in the time series illustrated in Figure 9 when compared with two previous structures.

3.6 Simulation results for the Small World network (Figure 10a) show that for population values of few hundreds and for large values of *m*, *MI* is large; while it has still a considerable difference to the maximum value 0.4 (as

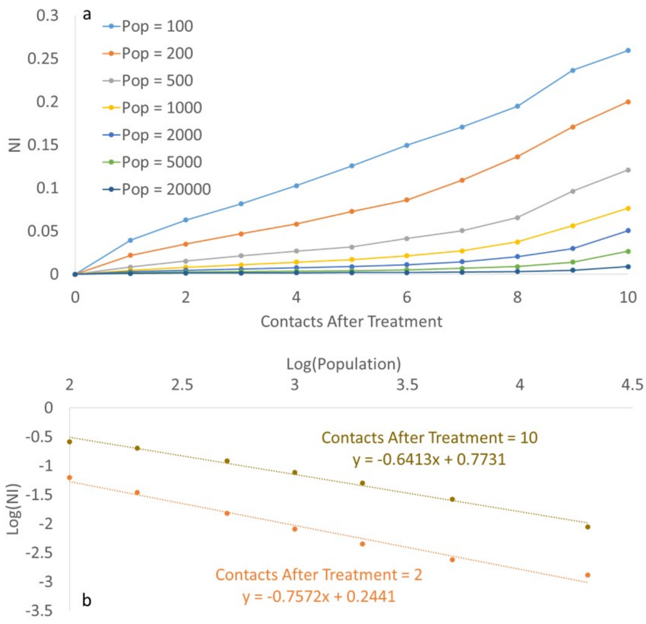

Figure 10: Simulation results for Small World. (a) Normalized spectral density for different "Contacts After Treatment", (b) log-log diagram showing the dependency of *NI* to population.

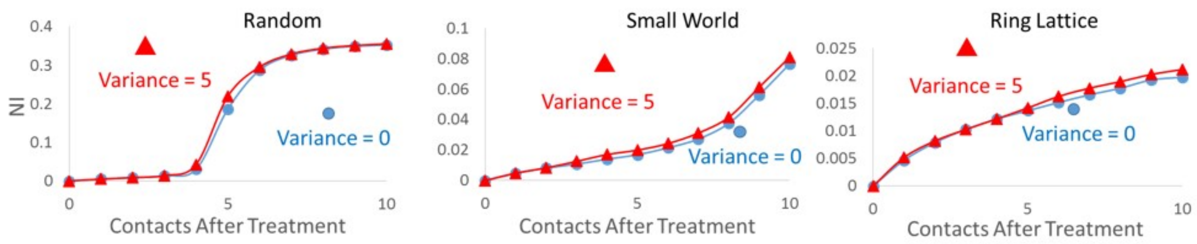

Figure 11: Sensitivity analysis of the results considering a normal random variable for the nodes' degree with variance 0 and 5. The population of the network was set to 1000.

calculated in the next section). Moreover, Figure 10b indicates that for small values of *m*, *MI* strongly depends on population and this dependency gradually decreases as m increases.

Sensitivity to the network homogeneity

3.7 In order to analyze the sensitivity of the results to the homogeneity of the nodes' degree, we assume each node's degree to be a normal variable with average 10 and variance 5. Figure 11 illustrates the comparison with the results of the homogenous model for different network structures.

3.8 As illustrated in Figure 11, the variation from the homogenous network is not significant, however this variation is relatively larger for the Ring Lattice network. The oscillations are a bit larger for the Ring Lattice network which can be due to the fact that the random distribution adds some longer links to the network.

Summary results

3.9 The above mentioned results are summarized in Table 2. This table presents qualitative results on collective behavior for different values of population and "Contacts After Treatment" (*m*).

	Low m	High m
Low population	Oscillation is observed in all network structures. The magnitude depends on population.	Oscillation depends on the network structure. (a) Random network: maximum oscillation (b) Ring Lattice: small oscillation (c) Small World: large oscillation
High population	Oscillation depends on the network structure. (a) Random network: small oscillation (b) Ring Lattice: no oscillation (c) Small World: no oscillation	Oscillation depends on the network structure. (a) Random network: maximum oscillation (b) Ring Lattice: no oscillation (c) Small World: large oscillation

Table 2: Summary of observed results in simulations.

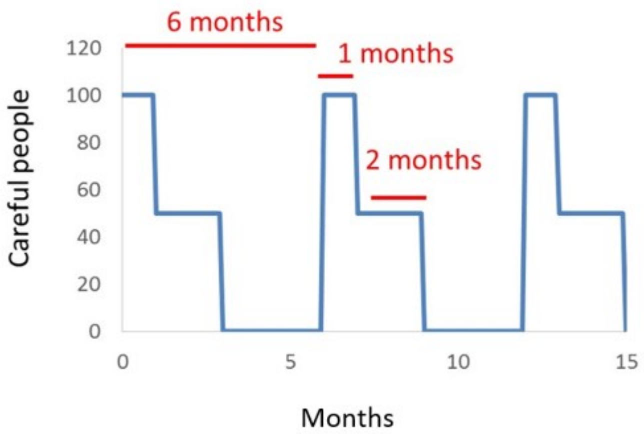

Figure 12: Time series for careful people in the extreme case when all people are promoted together. Note: We have assumed whole population contribute in the collective behavior and people become careful all together. Total population is set to 100.

Theory and Discussion

Oscillation origin

4.1 The origin of the observed simulated oscillations can be explained as follows. When there are many *careful* people, some of them randomly have a visit due to toothache or public HPP. If they need and receive treatment, they will talk about their experience with some friends and therefore more people will have visit afterwards. On the other hand, since agents usually become careless after a while (forget), the same iteration will happen again.

4.2 In extreme cases in which all people contribute in the collective behavior and become aware immediately all together, time series profile for careful people would be as illustrated in Figure 12. In this case, all people in the population are promoted, for visiting, together and go for check-ups. After one month in average, half of them who were not under treatment become careless, while the other half become careless after three months. NI_{max} for this extreme case is then found as follows:

$$NI_{max} \sim 0.4 \tag{12}$$

This relation roughly gives an upper bound for NI and as it was shown in results section, some of our simulation results converged to this value under specific conditions.

Oscillation condition

4.3 In order to find a rough approximation for the condition in which oscillation is observable, we consider the following scenario. Consider at time = 0 all agents are *careless* and *recently not visited* a dentist. Then, randomly one of them becomes *careful* and excited enough to encourage friends (after treatment) and successively, in

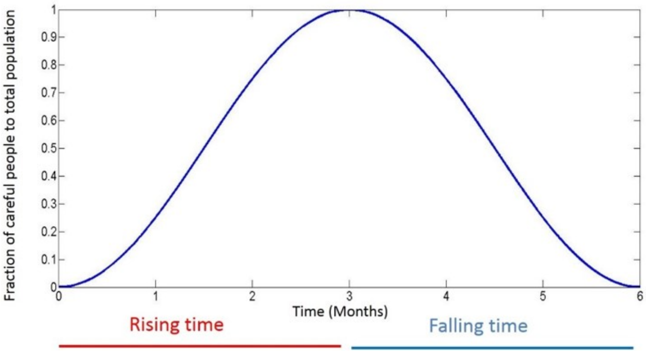

Figure 13: Schematic of the pattern of number of careful people when we have collective oscillatory behavior.Note: Most of the population are expected to become careful in the first three months. In the following sub sections, some simple relations for the oscillation condition in Random and Ring Lattice networks as two extreme situations are driven. Calculations for Small World networks are much more complicated, but we can simply consider it as a condition between Random and Ring Lattice networks.

chain reaction process of sending encouraging messages, a considerable amount of people become careful and go for check-ups. In order to observe the collective oscillatory pattern, with the $T_0 = 6$ months period, the chain reaction process speed must be large enough that in $\frac{T_0}{2} = 3$ (the first half of the total $T_0 = 6$ months period) most of the population become careful. This is when the number of careful people is expected to rise in oscillatory pattern (Figure 13). Otherwise, if a considerable amount of people remain careless after the initial three months, then the rising in number of careful people will continue in the second half of T_0, at the time when the collective oscillation is expected to fall; the oscillatory pattern is destroyed.

Random network

4.4 To formulate the oscillation condition for Random network, we consider a stepwise process where each time step has a length of T_t = "Treatment Time" assuming that at time $t = 0$ all people were careless and recently not visited dentist. At that time, one randomly chosen person becomes careful, pays a visit to a dentist, and then goes under treatment. After time step T_t, this patient encourages her friends to go for visit and the same process, as the last step, starts with larger number of patients. Consider we have n_k people who have already become careful and gone for visit until step *k*. From this population, $n_k \breve{} n_{k-1}$ individuals became careful in the step k and half of them (who need treatment) will encourage their friends in step $k+1$. Therefore, $nk+1$ can be calculated as follows:

$$n_{k+1} = n_k + \frac{C}{2}(n_k - n_{k-1})(1 - \frac{n_k}{N}) + r(N - n_k)T_t \tag{13}$$

where *C* is the number of encouraging messages that an excited person sends to her friends and *r* is the rate of "Toothache & HPP" transition.

4.5 The second term on the right hand side of the equation, which indicates the new careful agents due to WOM, counts the number of encouraging messages, $\frac{C(n_k)-n_{k-1}}{2}$, multiplied by the probability that the message receiving agent has not received any message in the previous steps, $\frac{1-n_k}{N}$. The factor $\frac{1}{2}$ in the above relation arises since we have assumed that half of the agents (Required Treatment probability, $RT = 0.5$) need treatment, and so will send encouraging messages. In addition, if there are *m* "Contacts After Treatment" and *L* network connections per agent (in our simulations L = 10), the agent will send a message back to the person who has just recently encouraged her with probability $\frac{m}{L}$. So *C* should be considered as $C = m - \frac{m}{L}$. The third term, in the above relation, counts the number of new *careful* agents due to random "Toothache & HPP" transition during one step. In our simulations, the rate of "Toothache & HPP" transition, r, was considered to be 0.025.

4.6 To find a simple, at the same time rough, approximation one can assume the early fast growing stages of the chain reaction process, $\frac{n_k}{N} << 1$ and also assume $C >> 1$ that means an agent sends encouraging messages to most friends. In this situation with $n_k >> n_{k-1}$ the discrete relation can be written as follow:

$$n_{k+1} - n_k = \frac{C}{2}n_k + rNT_t \tag{14}$$

4.7 Given that the total time for growing the number of careful people is about three months. this is much larger than the time length of each step (T_t = 0.5 months). Therefore, we can rewrite the above discrete relation in a continuous form as follows:

$$\frac{dn}{dt} = \frac{C}{2T_t}n + rN \tag{15}$$

4.8 By solving this differential equation, we easily find the condition in which most of the population is covered (become careful) in the first half of the total $T_0 = 6$ months of the oscillation period.

$$\ln \frac{C}{2T_t r} \leq \frac{CT_0}{4T_t} \tag{16}$$

4.9 Interestingly this condition is independent of *N*. In other words, in Random networks the oscillatory collective behavior will occur in the society if the above non-equality is satisfied no matter how large the population is. The above inequality is satisfied for a critical *C* value of C_{min} = 1.33 which almost corresponds to a critical m value of $m_{min} \sim 1.5$. It means that if each agent encourages at least 1.5 friends the collective oscillation is observable.

4.10 These theoretical results can be compared with simulation results presented in Figure 6. This Figures shows that for larger values of "Contacts After Treatment" (*m*) oscillation intensity is independent of population which is in complete agreement with the theory. It also shows that for these large values of *m*, the value of *NI* almost reaches its maximum value, $NI_{max} = 0.4$. The similarity between the oscillation's peaks shapes of Figure 5b (for m = 10) and Figure 12 is observable.

4.11 Also it can be seen that the oscillation intensity becomes considerable for values of m greater than 3. This shows that the theory underestimates the critical min value for the oscillation condition. This deviation can be due to the fact that in the approximations we have assumed that $C >> 1$.

Ring Lattice network

4.12 For Ring Lattice network, agents are placed on a ring and individuals become careful due to WOM locally. In this structure, there are some careful regions on the ring that grow by their two end sides. Assuming that half of the individuals who receive the encouraging message will need treatment and send the subsequent messages, we simply assume that a local careful region grows with $\frac{C}{2}$ agents at each step. It should be noted that this assumption is just a rough approximation for which we have avoided sophisticated calculations. The differential equation for *n* follows as:

$$\frac{dn}{dt} = \frac{C}{2T_t}D \tag{17a}$$

$$\frac{dD}{dt} = \frac{rN}{2} \tag{17b}$$

4.13 Where D is the number of careful regions. The first equation calculates the growth of D careful regions and the second equation is the rate in D increment due to the random "toothache and HPP" transition. The $1/2$ factor in the second equation comes from the fact that half of the randomly becoming careful individuals do not need treatment and so will not create an active careful region. It should be stated that as C is assumed to be large, and if the first randomly created active point of the arc is active, then the arc will remain active. It is also assumed that $n << N$. For the condition in which most of the agents become careful in first $\frac{T_0}{2}$ we find:

$$N \leq \frac{C}{4T_t}T_0 + \frac{NCr}{8T_t}(\frac{T_0}{2})^2 \tag{18}$$

4.14 The first term on the right hand side is relevant to the first careful region that is assumed to exist at $t = 0$. The second term appears due to the consequent careful regions forming randomly due to toothache and HPP. In contrast to Random network, this inequality strongly depends on population. For the maximum value of $C = 9$ we find a condition of $N < 30$ satisfies the oscillation condition. These results are in consistent with simulation results (Figure 8) where the oscillation intensities are much smaller than Random network and strongly depends on population. The simulation results show that for $N = 100$ we still have considerable oscillations. This deviation from theory can be due to the fact that the careful regions actually grow faster than the simple approximation rate $\frac{C}{2}$. It should also be noticed that for Small World network, as expected, Figure 10 shows

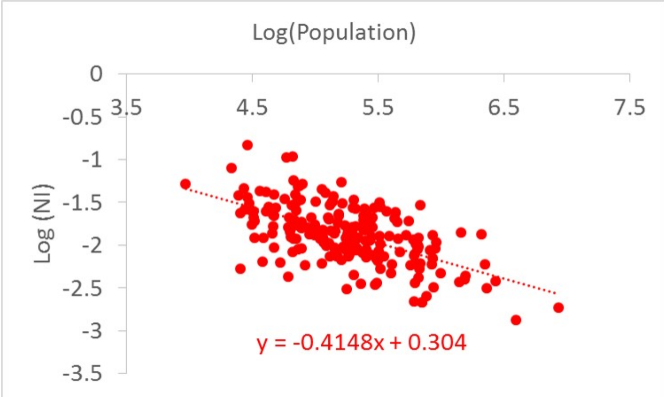

Figure 14: Data from Google Trends fitted to a linear relation between NI and Population in a log-log diagram.

that for small values of C the oscillation intensity is population dependent while this dependency gradually reduces as C increases. This result clearly reflects on the nature of the Small World network as a case between two extreme cases of Random and Ring Lattice networks.

Comparison with Empirical Data

5.1 To validate the model, the results are compared with an empirical data gathered from Google Trends service which reports the relative number of queries to search specific words by certain user defined time periods and locations. This service can be used to report the relative number of queries related to a specific category. In order to find a proper measure for the people's attention to oral health issues, choosing US society as a developed country with high level of access to Internet, we gathered the reports of the relative number of searches in the "Oral & Dental Care" category for 208 cities in US since early 2004. The names of cities in addition to their population can be found in Appendix. For each city, the report consisted of a time series showing the relative number of queries over time. The data indicates that oscillatory behavior and oscillations' intensity is population dependent. The relative reported numbers, showing the amount of searchers' attention to dental and oral health care issues, somehow reflect a measure of carefulness among the society. We assume that the relative amount of search queries is proportional to the number of careful people in our model. Calculating the power spectrum of the time series, we found the *NI* values for each city and by knowing its population size we could compare the data to the model results. In order to find a relation between *NI* and the population of the city, we found that the data best fits a linear relation in a log-log diagram. Figure 14 shows the fitted data and the linear regression statistical analysis results are illustrated in Table 3. The slope of the linear equation is -0.41 ± 0.08. Comparing the linear equations of the relevant model graphs (Figure 6b, Figure 8b, Figure 10b), it turns out that the simulation results for Ring Lattice and Small World network decrease much faster, as the population increases, compared with Google Trends data. The slope of the linear equation for Ring Lattice network is almost -0.8 for all of the values of "Contacts After Treatment" while for Small World the slope is at most -0.64, relevant to 10 contacts after treatment.

5.2 In the case of Random network, the simulations graphs cover a wide range of slope values from -0.8 to 0. The slope = -0.41, relevant to the Google data, occurs for a value between 4 and 5 number of contacts after treatment. It shows that the Google Trends data can fit the Random network model for "Contacts After Treatment" of about 4-5. The Google Trends data is compared to the Random model in Figure 15. It should be mentioned that, in order to fit better to the data, we have shifted the empirical point for about 0.7 to the left on the log(population) axis. This means that the model well explains the data if we assume that 20% of the population actually involve in the network. This fraction value can be regarded as an estimation for the fraction of the society engaged in the Internet based activities; they are deeply influenced by Internet social networks and use Internet as a significant source of information.

Conclusion

6.1 There are some empirical facts that show the effect of peer connections on individuals' health behaviors. In

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Upper 95.0%	Lower 95.0%
Intercept	0.303961	0.20830	1.4592	0.14603	-0.10673	0.71464	-0.10673	0.71464
X Variable	-0.4148	0.03950	-10.5009	6.2E-21	-0.49268	-0.33692	-0.49268	-0.33692

Table 3: Regression analysis of the Google Trends Data.

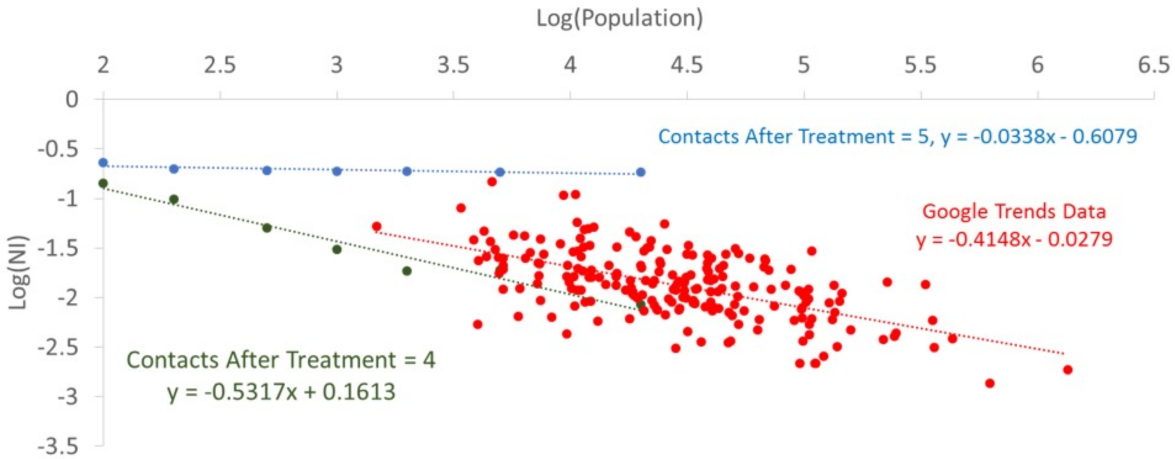

Figure 15: Simulation results fitted to linear relation between NI and population, in log-log diagram.

some cases, these individuals' behavior changes produce interesting collective behaviors, as emergent properties of the system, in the society level. One of these social emergences can be observed in the oscillatory pattern of the amount of demand for dental visiting in social networks. In the current work, an agent-based model is introduced to investigate this collective behavior. The model illustrates that this oscillatory pattern is strongly dependent upon the network structure and the number of effective connections. In Random networks, the oscillations appear as the number of effective contacts among agents exceeds a critical value of about 3, and interestingly for larger values of effective contacts the oscillation intensity reaches its maximum no matter how large the population is. In Ring Lattice networks, where we have local connections, the oscillation intensity is much smaller than Random network. In addition, in contrast to Random network the oscillatory pattern is strongly dependent on population in the Ring Lattice network. For Small World network the results are somehow a combination of the Random and Ring Lattice networks. Comparing the model results to empirical data from Google Trends, it turns out that the results best fit to Random network model while we assume that 20% of people are involved in the network in each US city. This suggests that the model can be used focusing on the fraction of people involved in Internet social networks and activities. As an insight, the model predicts that the dental health service demand oscillations may grow as people are more influenced by Internet social networks which may lead to resource management problems. Of course it should be noted that the model results are based on restricted assumptions; the model has ignored many other participants like suppliers and also demands from other parts of the society whom not using internet which may become significant in specific situations.

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Appendix

Table 4: 208 cities and regions in US for which the Google Trends data was gathered (Source: U.S. Census Bureau's 2014 Population Estimates).

City	Population
New York NY	8491079
Los Angeles CA	3928864
Chicago IL	2722389
San Francisco, Oakland, San Jose CA	2282029
Houston TX	2239558
Dallas, Ft. Worth TX	2093285
Philadelphia PA	1560297
Phoenix AZ	1537058
San Antonio TX	1436697
San Diego CA	1381069
Sacramento, Stockton, Modesto CA	996874
Austin TX	912791
Raleigh, Durham (Fayetteville) NC	895737
Seattle, Tacoma WA	873501
Jacksonville FL	853382
Indianapolis IN	848788
Columbus OH	835957
Charlotte NC	809958
Boston MA, Manchester NH	766332
Minneapolis St. Paul MN	704847
Washington DC (Hagerstown MD)	699257
Detroit MI	680250
El Paso TX	679036
Tampa, St. Petersburg (Sarasota) FL	666606
Denver CO	663862
Cleveland, Akron (Canton) OH	659677
Memphis TN	656861
Fresno, Visalia CA	645267
Nashville TN	644014
Greensboro, High Point, Winston Salem NC	630484
Albuquerque, Santa Fe NM	627466
Baltimore MD	622793
Oklahoma City OK	620602
Portland OR	619360
Las Vegas NV	613599
Louisville KY	612780
Miami Ft. Lauderdale FL	606345
Milwaukee WI	599462
Tucson (Sierra Vista) AZ	571778
Colorado Springs, Pueblo CO	554253
Norfolk, Portsmouth, Newport News VA	524394
Kansas City MO	470800
Atlanta GA	456002
Omaha NE	446599
Wichita, Hutchinson KS	430055
Ft. Smith, Fayetteville, Springdale, Rogers AR	429328
Harlingen, Weslaco, Brownsville, McAllen TX	425157
Orlando, Daytona Beach, Melbourne FL	403873
Tulsa OK	399682
New Orleans LA	384320

Bakersfield CA	368759
Honolulu HI	350399
Lincoln & Hastings, Kearney NE	330380
Cedar Rapids, Waterloo Iowa City & Dubuque IA	329410
Flint, Saginaw, Bay City MI	328163
Grand Rapids, Kalamazoo, Battle Creek MI	321547
Corpus Christi TX	320434
St. Louis MO	317419
Lexington KY	310797
Pittsburgh PA	305412
Anchorage AK	301010
Cincinnati OH	298165
Yakima, Pasco, Richland, Kennewick WA	292445
Huntsville, Decatur (Florence) AL	283882
Waco, Temple, Bryan TX	281872
Toledo OH	281031
Providence RI, New Bedford MA	273999
Des Moines, Ames IA	272486
Mobile AL, Pensacola (Ft. Walton Beach) FL	269301
Buffalo NY	258703
Ft. Wayne IN	258522
Hartford & New Haven CT	254987
Laredo TX	252309
Champaign & Springfield, Decatur IL	252086
Tyler, Longview(Lufkin & Nacogdoches) TX	250899
Richmond, Petersburg VA	250554
Madison WI	245691
Lubbock TX	243839
Little Rock. Pine Bluff AR	243038
Odessa. Midland TX	242634
Santa Barbara, Santa Maria, San Luis Obispo CA	241336
Reno NV	236995
Baton Rouge LA	228895
Montgomery (Selma) AL	220295
Boise ID	216282
Greenville, Spartanburg SC, Asheville NC, Anderson SC	214840
Albany, Schenectady, Troy NY	214412
Birmingham AL	212247
Spokane WA	212052
Rochester NY	209983
Tallahassee FL, Thomasville GA	206807
Wichita Falls TX & Lawton OK	202131
Columbus GA	200887
Shreveport LA	198242
Amarillo TX	197254
Augusta GA	196741
Peoria, Bloomington IL	194558
Springfield, Holyoke MA	194115
Salt Lake City UT	190884
Monterey, Salinas CA	184953
Knoxville TN	184281
Sioux Falls(Mitchell) SD	184279
Chico, Redding CA	180773
Roanoke, Lynchburg VA	178475
Harrisburg, Lancaster, Lebanon, York PA	177822
Chattanooga TN	173778
Beaumont, Port Arthur TX	172133
Jackson MS	171155

Springfield MO	165378
Minot, Bismarck, Dickinson(Williston) ND	163777
Eugene OR	160561
Columbia, Jefferson City MO	160038
Macon GA	153691
South Bend, Elkhart IN	152611
Alexandria LA	150575
Rockford IL	149123
West Palm Beach Ft. Pierce FL	147632
Savannah GA	144352
Syracuse NY	144263
Abilene, Sweetwater TX	141709
Dayton OH	141003
Davenport IA, Rock Island, Moline IL	139483
Yuma AZ, El Centro CA	137163
Tri, Cities	134352
Columbia SC	132067
Charleston SC	130113
Greenville, New Bern, Washington NC	129932
Gainesville FL	128460
Topeka KS	127215
Lafayette LA	126066
Fargo, Valley City ND	122539
Evansville IN	120346
La Crosse, Eau Claire WI	118122
Biloxi, Gulfport MS	116734
Green Bay, Appleton WI	116147
Wilkes Barre, Scranton PA	116095
Lansing MI	114620
Wilmington NC	113657
Idaho Falls, Pocatello ID	112983
Duluth MN, Superior WI	112943
Billings MT	108869
Medford, Klamath Falls OR	99676
Erie PA	99452
Charleston, Huntington WV	99211
San Angelo TX	98975
Ft. Myers, Naples FL	91886
Portland, Auburn ME	89578
Bend OR	84080
Sioux City IA	82511
Grand Junction, Montrose CO	79255
Cheyenne WY, Scottsbluff NE	77720
Paducah KY, Cape Girardeau MO, Harrisburg, Mount Vernon IL	77615
St. Joseph MO	76967
Butte, Bozeman MT	76340
Albany GA	75769
Lake Charles LA	74889
Rapid City SD	72638
Jonesboro AR	72210
Burlington VT, Plattsburgh NY	71552
Casper, Riverton WY	71039
Columbus, Tupelo, West Point MS	70029
Missoula MT	69821
Quincy IL, Hannibal MO, Keokuk IA	69390
Monroe LA, El Dorado AR	67953
Florence, Myrtle Beach SC	67953
Jackson TN	67319

Dothan AL	67180
Victoria TX	66094
Johnstown, Altoona PA	65742
Youngstown OH	65062
Joplin MO, Pittsburg KS	64698
Rochester MN, Mason City IA, Austin MN	63576
Bowling Green KY	62479
Utica NY	61332
Terre Haute IN	60956
Hattiesburg, Laurel MS	60688
Great Falls MT	59152
Sherman TX, Ada OK	57073
Harrisonburg VA	52478
Greenwood, Greenville MS	48434
Palm Springs CA	46854
Wausau, Rhinelander WI	46799
Twin Falls ID	46528
Binghamton NY	46299
Wheeling WV, Steubenville OH	45822
Charlottesville VA	45593
Ottumwa IA, Kirksville MO	42315
Mankato MN	40411
Meridian MS	40196
Lima OH	38265
Panama City FL	37681
Bluefield, Beckley, Oak Hill WV	35861
Bangor ME	32568
Salisbury MD	32563
Fairbanks AK	32469
Juneau AK	32406
Clarksburg, Weston WV	31230
Parkersburg WV	30981
Helena MT	29943
Alpena MI	28988
Elmira NY	28647
Watertown NY	27590
Eureka CA	26925
Zanesville OH	25372
Traverse City, Cadillac MI	25187
North Platte NE	24327
Marquette MI	21441
Presque Isle ME	9317

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