

Diffusion Follows Structure – A Network Model of the Software Market

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ABSTRACT

By conducting simulations, we show that the structure of the personal networks significantly influences the diffusion processes in network effect markets like the software market. Varying connectivity (number of links to other participants), the heterogeneity of preferences, and the price, we analyze networks with two different topologies. The first topology is determined by linking consumers with their closest neighbors (“close topology”). For the second topology the links are determined randomly (“random topology”). For both topologies, the concentration of market share strongly correlates with the connectivity. The “random topology” leads to total market concentration even with very small connectivity. In contrast, diffusion within networks with close topology results in larger diversity of products; here, we find total market concentration only for very high connectivity.

1. Introduction

The software market with an estimated volume of more than 300 billion dollars in 1997 [10] is one of the most important markets of today’s world. Various vendors of any size compete for market share by producing innovations that might solve existing problems in a better way. A recent example of the dynamics of the software market is the emergence of the new Internet standard XML and various related product innovations. The W3C recommended this standard in February 1998 and about a year later it already experienced a dramatic acceptance with all large software vendors planning to develop new products with extended functionality.

The diffusion of innovations in the software market is strongly influenced by positive network effects, i.e.

the willingness to adopt a product innovation positively correlates with the number of existing adopters.

On the one hand, *indirect* network effects in the software market result from the fact that the benefit from a certain software application increases the more complementary goods and services are available. Software products are generally part of networks which have vertical (application - OS - hardware) or horizontal (database - word processing - spreadsheet - etc.) interdependencies to other software (and hardware) tools or products [9].

On the other hand, the need to exchange data and documents within a company or with external business partners leads to strong *direct* network effects. The more potential communication partners exist that use software compatible to the own system, the greater the chances for an easy and efficient data transfer (for an analytical analysis of standards in communication networks refer to [3] or [29]). Strategic units of large companies like the Lufthansa AG develop incentive strategies to unify office software applications within the company, because incompatibilities between office suites of different vendors have negative impact on document management (*Standardization strategies in large enterprises*, workshop with Lufthansa AG, Siemens AG, and the Institute of Information Systems at Frankfurt University, May 17th, 1999). Furthermore, the continuing discussion in the area of EDI concerning data formats and transmission technology is a good example for the significance of compatibility for business interaction. The importance of (product) innovation in this context becomes obvious looking at the new emerging Internet standard XML which is gaining relevance in the market fast.

If consumers¹ of software products are seen as participants in a communication network it seems likely that the diffusion of innovations is dependent on the characteristics of their communication partners, the density of the network and the intensity of interaction. For example, recent empirical studies indicate the existence of standardization pressure among business partners and that the direct network effects vary dependent on whether adopters within the individual network of business partners or within the entire market network (installed base) are taken into account [24], [28]. Business networks like in the automobile industry are good examples of this. Generally, we find strong communication in the network around large automobile vendors. This makes it favorable if not necessary to use compatible software standards. The network structure is dense connecting the vendor with its suppliers who in turn might be connected with suppliers of lower levels. This structure makes it more likely that certain software standards, probably proposed or enforced by a strong vendor, diffuse faster than they would in other industries with less density and less hierarchical structure. With increasing integration of business partners, interesting software products in this context are not only EDI solutions, but also standard software like enterprise resource planning (ERP) systems (e.g. SAP or Peoplesoft) or new XML-based document management systems.

While the phenomenon of positive network effects is analyzed in many economic publications, the existing approaches seem to be insufficient to explain important phenomena of the software market like the coexistence of different software products despite strong network effects, small but stable clusters of users of a certain solution or the phenomenon that strong players in communication networks force other participants to use a certain software.

Aiming at a better explanation of real world phenomena, we will develop a diffusion model for the software market. Our main hypothesis is that diffusion processes in the software market are significantly influenced by personal communication relationships of the potential consumers.

In the following section we will analyze whether existing models offer helpful concepts for our approach. In section 4 we will develop a network diffusion model of the software market and conduct simulations to substantiate our earlier findings. At the end of this work we will summarize the results and give an outlook on further research.

¹ Knowing that the term “consumer” is not appropriate for companies buying software products, we decided to use it anyway, since it is common in network effect literature.

2. Existing Approaches

Searching for appropriate instruments to model the software market, two areas of research seem to be promising. On the one hand, *theory of positive network effects* analyses the specific characteristics of markets for network effects goods. On the other hand, *diffusion models* focus on explaining and forecasting the adoption process of innovations over time.

2.1. Theory of positive network effects

We examined selected existing approaches in the area of the theory of positive network effects. We distinguished between empirical and theoretical research (for a more detailed distinction refer to [15]). Table 1 and table 2 show the objectives of common models. Also, the way how network effects are considered is shortly described. Although the list is exemplary, it gives a good overview of the benefits and restrictions of existing approaches and whether they might be helpful for our approach.

Existing theoretical models of positive network effects focus on individual buying decisions, marketing strategies of competing vendors, supply and demand equilibria, and welfare implications. The research results offer a good basis for analyzing network effects in a general way. Nevertheless, the models are in many ways not sufficient to model diffusion processes of software innovations. The examination of network effects in markets is done in a rather general way. Simple distinction between direct and indirect network effects alone is not detailed enough for an analysis of demand behavior in the software market. In contrast to the real world where communication within the individual communication network is a very important issue for decisions on software, direct network effects are considered in the utility function of individual consumers only as the aggregated number of users in a market (installed base). Personal networks in comparison to the whole market are not in the center of attention. Most of the models focus on equilibrium analysis and welfare implications. Some approaches analyze possible implications on marketing strategies, but the consideration of findings from network diffusion approaches like the two-step flow hypothesis [13], [20], [27] are missing.

Looking at existing empirical research (table 2), we find approaches that explicitly analyze software products. Some authors assume that network effects derive from product characteristics like interfaces for data exchange with other applications. By applying the hedonic pricing approach, the hypothesis that the existence of such attributes increases the willingness to pay for the respective product is statistically proven (for a more comprehensive discussion refer to [8]).

	Objective	modeling network effects
Rohlfs (1974) [21]	equilibrium analysis of network effect goods, development of cumulated demand functions	expected installed base $q_i^D = q_i^D(p, q_1, \dots, q_{i-1}, q_{i+1}, \dots, q_n)$
Katz/Shapiro (1985) [14]	welfare (efficiency) analysis, effect of network effects on competition and market equilibrium	installed base: $U=r+v(y^e)-p$
Farrell/Saloner (1986) [6]	equilibrium analysis, welfare (efficiency) analysis, excess inertia and excess momentum in case of competing technologies	installed base: $u(x) = a+bx$
Athur (1989) [1]	influence of increasing constant and diminishing network effects on market equilibria, relevance of path dependency	existing installed base: $u(A) = a+sn_A$
Wiese (1991) [30]	duopol simulation model for markets with network effects, price strategy as Nash equilibrium	installed base: $U(\text{indiv. preference}, n^e, p)$
Church/Gandal (1996) [4]	equilibrium and welfare analysis of indirect network effects, the role of software in case of incompatible competing hardware systems	network effects dependent on interdependencies between hard- and software, not dependent on network size
Gröhn (1997, 1999) [9] [10]	analysis of network effects and market failure in the software market	installed base: $N(x) = A+zx$

Table 1. Theoretical approaches to model network effect goods.

	objective	modeling network effects
Hartmann/Teece (1990) [11]	hardware (observation 1976-83): hedonic price function dependent on installed base	proof of network effects in the hardware market through regression
Gandal (1994) [7]	analysis of spreadsheet software (panel data 1986-91), proves the existence of network effects empirically: estimation of hedonic price function	proof of network effects in the software market through regression
Economides/Himmelberg (1995) [5]	analysis of fax machines (observation, census data 1979-92), estimation of equilibrium size of competing networks dependent on income and installed base	installed base: $u(y, n^e)$, empirical evaluation of the model
Moch (1995) [19]	database software (observation 1986-94): evaluation of relevant (quality and network effect) characteristics through estimation of hedonic price function	proof of network effects in the software market through regression
Gröhn (1999) [10]	word processing (observation of software tests in magazines 1985-95), proves the existence of network effects empirically: estimation of hedonic price function	proof of network effects in the software market through regression

Table 2. Empirical approaches to model network effects goods.

The results indicate the existence of network effects in the software market but do not give relevant help for our network diffusion approach.

2.2. Diffusion models

The economic analysis of diffusion focuses on describing and forecasting the diffusion of innovations in markets. In particular, the question arises which factors influence the speed and specific course of diffusion processes [26]. Traditional diffusion models are based on similar assumptions (for a comprehensive overview of the traditional diffusion models refer to [17]). Generally, the number of new adopters in a certain period of time is modeled as the proportion of the group of market

participants that did not adopt yet. Three approaches are most common [16, pp. 706-740], [18, pp. 12-26], [26]: The *exponential diffusion model* (also *external influence model* or *pure innovative model*) assumes that the number of new adopters is determined by influences from outside the system, e.g. mass communication. The *logistic diffusion model* (also *internal influence model* or *pure imitative model*) assumes that the decision to become a new adopter is only determined by the positive influence of existing adopters (e.g. word of mouth). The *semilogistic diffusion model* (also *mixed influence model*) considers both, internal and external influences. A famous example of the latter is the *Bass model*, which has been used for forecasting innovation diffusion in various areas such as retail service, industrial technol-

ogy, agricultural, educational, pharmaceutical, and consumer durable goods markets [2], [17].

Despite the existence of various diffusion models, the approaches are not sufficient to model the diffusion of network effect products. Schoder names three areas of deficits [22, pp. 46-50]. First of all, there is a lack of analysis concerning the phenomenon of critical mass. Furthermore, the traditional diffusion models are not able to explain the phenomenological variety of diffusion courses. Third, the models do not sufficiently consider the interaction of potential adopters within their socio-economical environment, how adoption changes relationship to other participants of the system, and how the willingness to pay a certain price changes with an adoption within a certain group.

Help for analyzing the relevance of interaction in diffusion processes comes from research activities in the area of network models of diffusion of innovations [25]. *Relational models* and *structural models* are two important approaches in this area. Relational models analyze how direct contacts between participants of networks influence the decision to adopt or not adopt an innovation. In contrast, structural models focus on the pattern of all relations and show how the structural characteristics of a social system determine the diffusion process. Table 3 shows common concepts of these models [25, pp. 31-61].

Relational Diffusion Network Models	Structural Diffusion Network Models
<ul style="list-style-type: none"> • opinion leadership • group membership • personal netw. density • personal netw. exposure 	<ul style="list-style-type: none"> • centrality • position equivalence • structural equivalence

Table 3. Concepts of relational and structural diffusion network models.

In this paper, we will focus on the relational models and therefore shortly describe the concepts of opinion leadership, group membership, personal network density, and personal network exposure, since these will be important for designing our simulation model. The *opinion leadership* concept assumes that some individuals in networks have strong influence on the adoption decision of many others. The approach is the foundation of market penetration strategies such as the two-step flow strategy where vendors first influence opinion leaders in a market who then influence their opinion followers. The concept of *group membership* analyzes the relevance of intra-group pressure towards conformity. The *personal network density* model measures the influence of how the connectivity of one network participant (i.e. the number of connections to other participants) or of the whole network (average number of

links) influences the spread of innovations. The *personal network exposure* is a measure of how intense an individual is exposed to an innovation, i.e. how many of his or her links lead to an adopter of a certain innovation. This is exactly the basic assumption of positive network externalities: the likelihood of adoption gets higher with increasing personal network exposure. These concepts seem quite useful for our analysis.

Summarizing the results of our literature analysis, we come to the conclusion that existing models only highlight certain areas of software diffusion. Nevertheless, combining some of the basic ideas and extending them on the basis of our empirical research seems very promising.

3. Network Diffusion Model of the Software Market

3.1. Basic model

Basis of our simulation is a simple model of the buying decision in network effect markets. The terminology is similar to the model of Katz/Shapiro [14], but we will interpret the terms differently. Let r denote the stand-alone utility of a network effect product (i.e. the willingness to pay even if no other users in the market exist) and $f(x)$ denote the additional network effect benefits (i.e. the value of the externality when x is the number of other adopters). For reasons of simplification we assume that all network participants have the same function $f(x)$, i.e. their evaluation of network benefits is identical. We also assume that the network effects increase linearly, i.e. $f(x)$ increases by a certain amount with every new user. The willingness to pay for a software product can then be described by the term $r+f(x)$. Let p be the price or the cost of a certain software product/solution, then a consumer buys the solution if $r+f(x)-p > 0$. In case of v competing products in a market, the consumer buys the product with the maximum surplus in case this exceeds 0:

$$\max_{i \in \{1, \dots, v\}} \{r_i + f(x_i) - p_i\}$$

If the surplus is negative for all i then no product is bought. Term (1) implies that only one product is used at the same time. This is a common assumption in many network effect models [e.g. 31, p. 10]. It also seems to make sense for the software market since it would be rather unusual to buy and use two different software product with the same functionality (e.g. Microsoft Office and Lotus Smart Suite) at the same time.

Unlike most of the existing models for markets with network effects, we want to conduct simulations by modeling the software market as a relational diffusion

network. In such networks the buying decision is not influenced by the installed base within the whole network, but rather by the adoption decisions within the personal communication network. The significance of this for buying decisions can simply be demonstrated by the following example. Figure 1 shows the communication network environment of consumer A who wants to buy a software product that serves her individual needs.

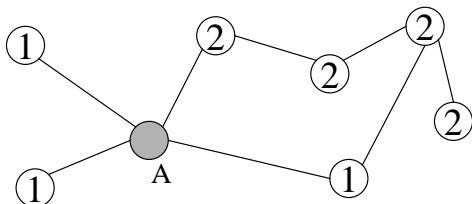


Figure 1. Communication network environment of consumer A.

There is a choice of two products (1 and 2) in the market. We assume that both products are for free and have identical functionality so that the buying decision only depends on the network effects. Applying traditional models that base the decision whether to adopt an innovation on the size of the installed base, consumer A would buy product 2 since the installed base with 4 existing adopters is larger. If we use the relational network approach and therefore only focus on the relevant communication partners of A, the consumer will decide to buy product 1 since the majority of his direct communication partners uses this solution.

Of course, this example is of rather general nature. In the following, we will prove the importance of personal network structure systematically by conducting simulations. Additionally, we will analyze how varying price and heterogeneity of individual preferences influence diffusion processes of competing software.

3.2. Simulation design

Our simulations are based on the assumption that network structure, the consumers preferences and the prices of the software are constant during the diffusion process. All the results presented below are based on a network size of 1,000 consumers. We also tested our simulations for other network sizes without significant difference in the general results. We conducted 6,000 simulation runs, 3,000 each for low price and for high price software, respectively. All entities of our model were implemented in JAVA 1.1 and their behavior was simulated on a discrete event basis.

Network Structure. First, the n consumers are distributed randomly on the unit square, i.e. their x - and y -coordinates get sampled from a uniform distribution over $[0; 1]$. In a second step, the network's structure is generated by either choosing the c closest neighbors

measured by euclidean distance (*close topology*) or selecting c neighbors randomly from all $n-1$ possible neighbors (*random topology*). This distinction is made to support the central hypothesis of our paper, namely: *Ceteris paribus* (e.g. for the same network *size* and *connectivity*) the *specific* neighborhood structure of the network strongly influences the diffusion processes.

The graphs in figure 2 exemplary show randomly sampled cases of the *close topology* (exemplary for 100 consumers and a connectivity c of two, five and ten respectively). As we see, a low number of neighbors may lead to a network structure which is not fully connected, i.e. its consumers can only experience network externalities within their local cluster. The standardization processes in individual clusters can not diffuse to any consumer of a different cluster. These "sub-populations" evolve in total separation and it is therefore rather unlikely, that all the isolated regions evolve to the same global standard. With increasing connectivity (five or ten neighbors), the chances that a network is not connected gets rather small, i.e. every sub-group of consumers, agreeing on a specific product, may "convince" their direct neighbor clusters to join them. The "domino effects" finally might reach every consumer even in the most remote area of the network. However, the number of "dominos" that have to fall before a standard which emerged far away in a certain area of the network reaches the local environment of an actor and therefore influences the decision to adopt is typically much higher than in the corresponding graph with *random topology*. Speaking more formally, the average length of the shortest path connecting two arbitrarily chosen vertices of the graph (i.e. the number of neighbors you have to traverse) is smaller for the same connectivity if the graph has a random topology.

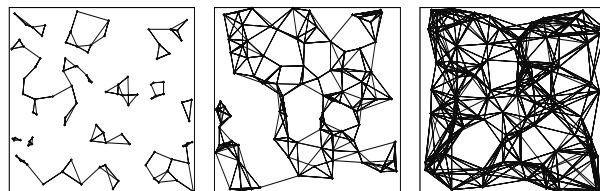


Figure 2. Typical networks with two, five or ten closest neighbors (close topology).

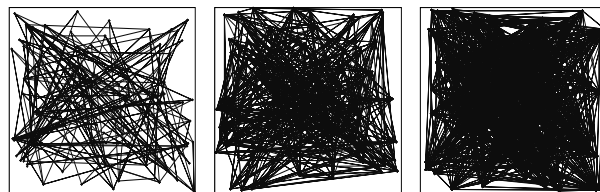


Figure 3. Typical networks with two, five or ten random neighbors (random topology).

Figure 3 shows the graphs with the same connectivity (2, 5, and 10) but *random* topology. The optical impression of a higher connectivity (which is an illusion) results from the fact that we selected "neighbors" to represent an asymmetric relation. That is, when consumer x gets positive external effects by a neighbor y , it is unlikely in the *random* topology that vice versa, y also gets positive effects from x . Of course, within the *close* topology symmetric neighborhood is more common meaning that there is a higher probability that if y is the closest neighbor from the perspective of x , at the same time x is also the closest neighbor from the perspective of y . In this case the two links are plotted on top of each other and that is why the close topology graphs look less connected.

Of course, most real-world networks represent an intermediate version of these extreme types, but since the costs of bridging geographic distance get less and less important the more information technology evolves, the tendency is clear. Electronic markets will rather resemble the *random* type of structure (since we select our partners by other criteria than geographical distance), while in markets for physical goods (or face to face communication) the physical proximity is still a very important factor for selecting business partners and therefore, the *close* topology will be a good proxy to the real world network structure.

Preferences, Prices, and Network Effects. Regardless of topology, in our simulation, every consumer can choose from all existing software products and knows all their prices. Initially, all consumers are (randomly) equipped with one software product, which may be considered to be their "legacy software" that is already installed and does not cause any further cost.

The direct utility that each consumer draws from the functionality of the v different products is then sampled from a uniform random distribution over the interval $[0;util]$. For each consumer and every software we use the same interval. Thus, a value of $util=0$ leads to homogeneous direct preferences (of zero) while the higher the exogenously given value of $util$, the more heterogeneous the preferences of the consumers get (with respect to the different software products as well as with respect to the neighbors they communicate with).

The weight of the positive network externalities deriving from each neighbor using the same software has been set to an arbitrary (but constant) value of 10,000 (for every consumer and every run).

In order to isolate the network externalities and heterogeneity of consumer preferences from other effects, we decided to fix all prices for the software products to a constant value and all marketing expenditures to zero for the simulations presented here, i.e. consumers decide solely upon potential differences of *direct utility* and the *adoption choices of their neighbors* (see term (1)).

Dynamics of the decision process. In each iteration of the diffusion, every consumer decides whether to keep her old software or whether to buy a new one based on the decision rationale described above (see term (1)). The old software is assumed to be discarded once a new one is bought, i.e. it can neither provide the deciding consumer with direct utility nor the neighbors with positive externalities anymore. The adoption decisions are made in a sequential order, i.e. all consumers may always be assumed to have correct knowledge about the software their neighbors are currently running. Although we have not yet established a formal proof, for our simulations this decision process always converged towards an equilibrium in which no actor wanted to revise his decision anymore. We did not experience any oscillation.

3.3. Results of simulating the diffusion process

First, a total number of 3,000 independent simulations were run with 1,000 consumers and 10 different software products until an equilibrium was reached. The distribution reached in this equilibrium was then condensed into the Herfindahl² index used in industrial economics to measure market concentration (e.g. [23]). In the following diagrams, every small circle represents one observation.

The top diagram in figure 4 illustrates the strong correlation (0.756) of connectivity and equilibrium concentration for *close topology*. Despite of this strong correlation it can clearly be seen that even in networks with 200 neighbors per consumer (i.e. a connectivity of 200) the chances are still very low that one product completely dominates the market. For *random topologies* (figure 4, bottom) an even stronger correlation (0.781) is obtained. Note that all the correlation illustrated in this paper are significant on the 0.01 level.

Note that the scale of connectivity is extremely different in the two graphs of figure 4. It is obvious that the likelihood for total diffusion of only one software product is very high in random topology network even for very low connectivity. Since the diagrams simply plot all circles on top of each other, the optical impression of the very frequent observation of a 1.0 concentration (in the top right corner of the graphs) is distorted. The results will optically become clearer in the 3-dimensional graph of figure 5.

² The Herfindahl index is calculated by summing up the squared market share for each vendor. If all market shares are evenly distributed among our ten alternative products, we get the minimal concentration index of $10 \cdot (0.1)^2 = 0.1$ while we get a maximal concentration index of $1 \cdot 1^2 + 9 \cdot 0^2 = 1$ if the diffusion process converges to all consumers using one identical software product.

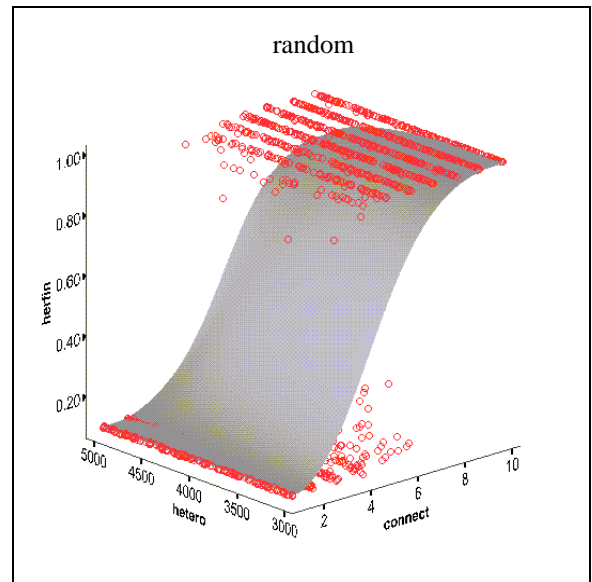
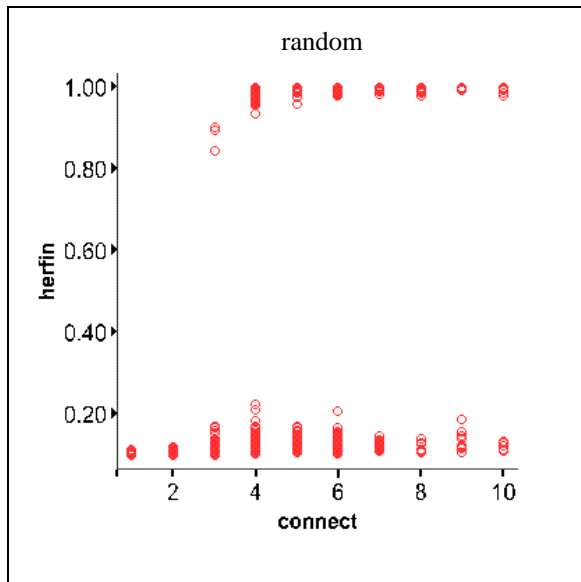
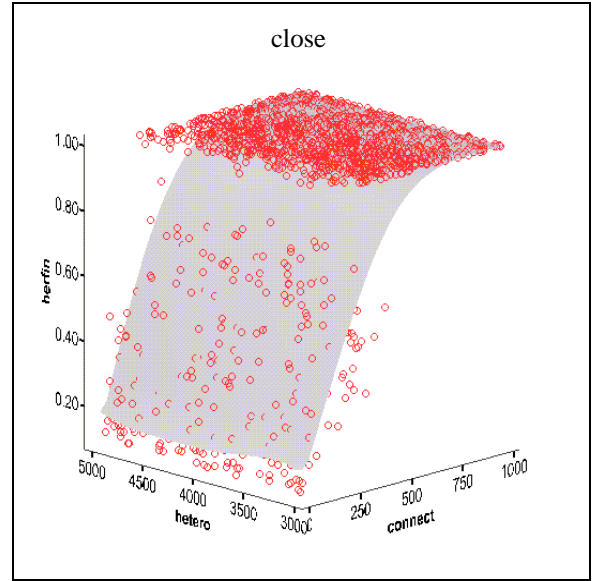
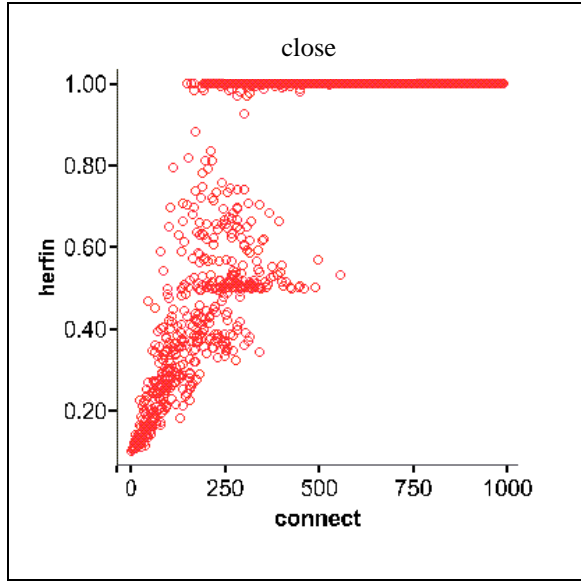


Figure 4. Strong correlation of connectivity and concentration for close and random topologies.

Figure 5. Equilibria in close topology and random topology networks.

In figure 5 we additionally consider the *heterogeneity of preferences* in the analysis as a third dimension. We did not find any significant dependency of the sampled equilibria on this factor for *close topologies* (figure 5, top). However, this changes if we sample networks with *random topologies*. Here we found slight but significant negative correlation of heterogeneity and concentration (-0.141).

Note that the axis for connectivity again is scaled from 1 to 10 neighbors in the bottom diagrams in figure 4 and 5. It can clearly be seen that already for 10 neighbors per consumer (1% of the total population) it is almost certain that only one product will finally take over the whole market (figure 5, bottom).

Comparing this with the top graph where the probability of reaching a concentration higher than 0.2 is almost zero for the same connectivity *strongly* supports our hypothesis that for a given connectivity the indirect domino effects are much stronger for *random* topology networks and thus the diffusion process shows much higher tendencies towards standardization. To test this statistically, we ran a Kolmogorov-Smirnov test [12, p. 520-524] rejecting the hypothesis that the concentration indices obtained for close and random topologies follow the same distribution on a significance level better than 0.0005 (KS-Z of 2.261). This result substantiates our findings statistically.

A second interesting phenomenon can be seen in the fact, that although the mean concentration for a *random* topology networks of connectivity 5 is about 0.5, there are hardly any equilibria with concentration indices between 0.2 and 0.8, i.e. either the diffusion process leads to one strong product or many products will survive. This is different for *close* topology models where intermediate solutions with two or three strong products can be stable equilibria, obviously being the result of sub-groups of consumers (with strong intra-group communication and fewer links to other groups) collectively resisting external pressure to switch their selected product.

Summarizing our findings so far, we display four typical patterns for diffusion processes towards an equilibrium depending on network topology and heterogeneity of preferences (figure 6). The x-axis shows the number of iterations with every consumer deciding once per iteration. The y-axis illustrates the market shares of the 10 software products. Note that as discussed above the *random / heterogeneous* case is one of the rare intermediate cases (in figure 5, bottom, it can be seen that there are hardly any equilibria for a connectivity of 5 and a concentration between 0.1 and 1.0).

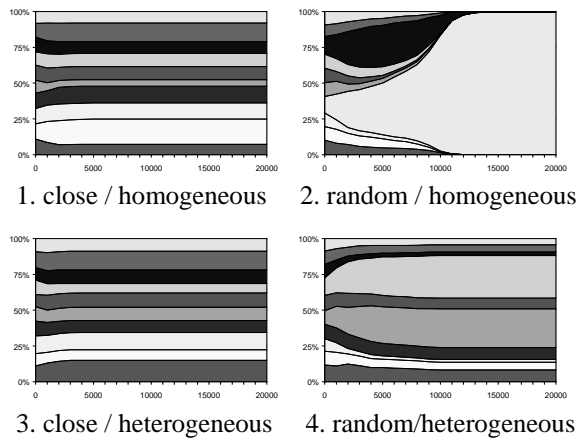


Figure 6. Typical diffusion processes for 1,000 consumers and connectivity of 5 depending on topology and heterogeneity of preferences.

The influence of topology on the diffusion of innovations in networks is obvious. While the *close* topology generally is the basis for a greater diversity of products since cluster or groups of consumers can be relatively independent from diffusion processes in the rest of the market, the *random* topology tends to market dominance of one or few products.

As we already mentioned, for every run all prices were fixed to the same constant value for all products. For the processes simulated above this constant price has been chosen to be \$50, which means switching to another software is very cheap compared to the positive

externalities from neighbors (worth \$10,000) if they use the same product.

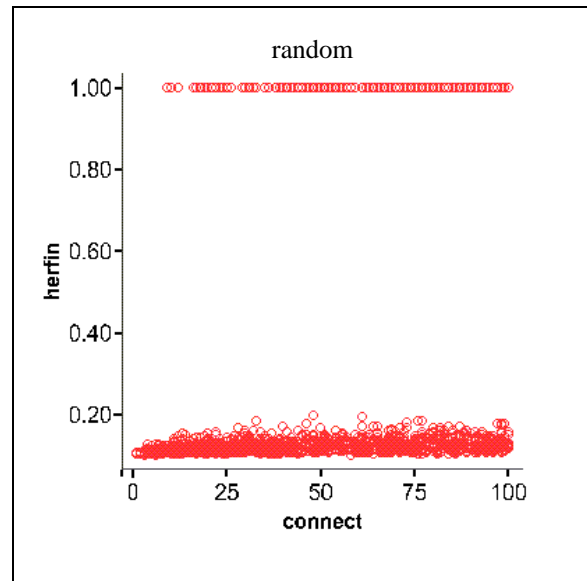
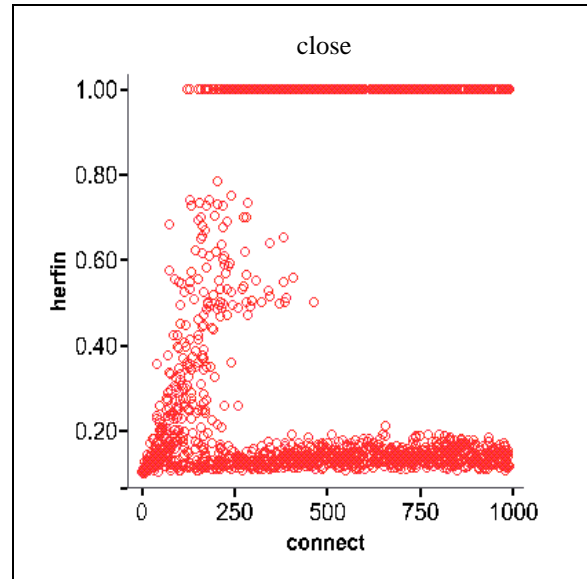


Figure 7. High prices lead to stronger inertia to switch and less concentration for close and random topologies.

While this may be the correct model for competing shareware e-mail tools, or free internet-based phone or meeting software, for many software products the ratio of price towards positive network externalities is less extreme. Increasing the prices (while still being identical for all products) will of course lead to higher inertia of the consumers to buy a new product despite all of the neighbors using it. If we select too high a price, everyone sticks to his initial solution and there is no diffusion process at all. Therefore, after some test simulations we

tried to select a "critical value" as the constant price by fixing it to the consumer's expected direct utility. Thus, whenever we sample direct utility from the interval $[0;util]$ we fix the price of every products to $0.5*util$. This means that for about half of the consumers the direct utility from owning a specific product would not compensate for the costs as long as there are no neighbors yielding any network effects. The high number of processes that end in a low concentration equilibrium even for high connectivity (fig. 7) supports this rationale when we compare our results to the processes obtained for low price software (fig. 4 and 5). Note, that in the bottom graph the x-axis only scales up to 100 neighbors.

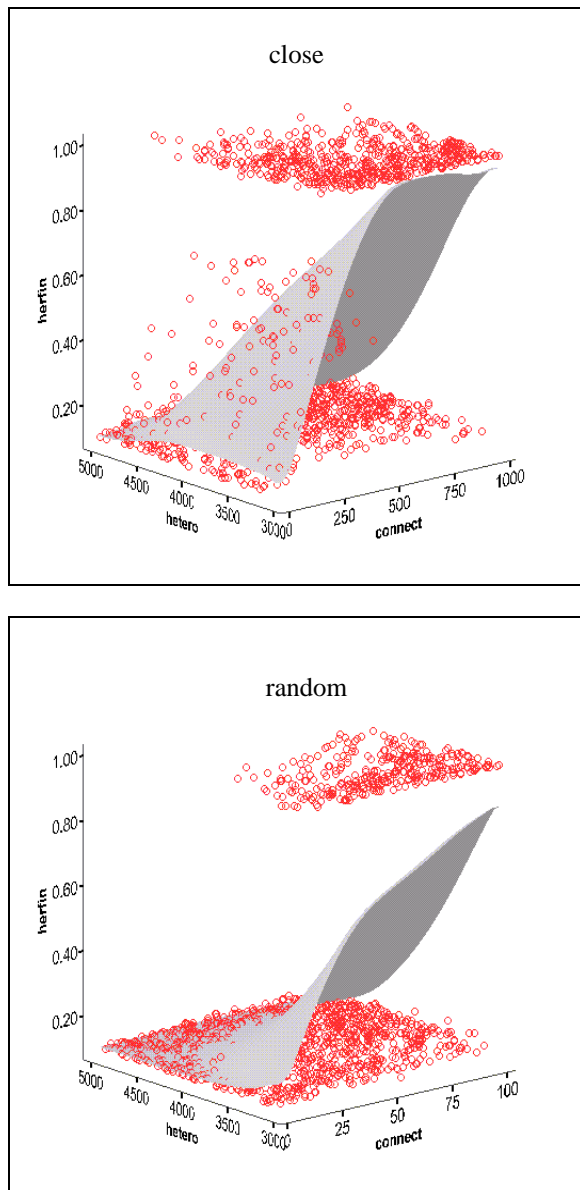


Figure 8. Equilibria in close and random topology networks for high price software.

We still get more 1.0 concentration equilibria (total diffusion of one product) for random topologies than for close topologies. Nevertheless, even for random topologies the inertia effect is very strong. However, for both topologies there still is a significant positive correlation of connectivity and concentration (0.120 for close and 0.231 for random) although much weaker than for the low price markets. Please note again that the graphs of figure 7 display plots on top of each other resulting in optical distortion, which will be resolved in the 3-dimensional graph in figure 8.

Another very interesting effect can be observed if we additionally consider *heterogeneity of preferences* (figure 8). In contrast to figure 5, we find a much higher negative correlation, significant for both, *close* (-0.611) and *random* (-0.500) topologies. Although higher heterogeneity has the positive effect of increased utility surplus for some consumers, others get even more reluctant to pay the high price, when there are no neighbors yet sharing this products. Thus, they resist much longer to any domino effects. Whether or not the domino effect may circumvent these resistant single nodes or clusters and still diffuse again heavily depends on the chosen network topology.

4. Conclusions and further research

By conducting simulations we demonstrated that the structure (connectivity and topology) of the personal networks significantly influences the diffusion processes in software markets. Varying connectivity, the heterogeneity of preferences, and price, we analyzed networks with two different topologies. The close topology was determined by linking a certain number of consumers determined by closest neighbor relationships. These networks were compared to networks within which a certain number of links were randomly generated (random topology). For both topologies the concentration of market share correlated strongly with the connectivity.

The random topology led to total market concentration even with very small connectivity. In contrast, diffusion within networks with close topology resulted in larger diversity of products; here, we found total market concentration only for very high connectivity. After substantiating these results through statistical tests, we accepted our research hypothesis that the *specific* neighborhood structure of actors in software markets strongly influences the diffusion processes.

We plan further research on the basis of our findings. First, we want to demonstrate the influence of complementary goods in the market. Therefore, we will integrate the concept of indirect network effects into our simulation model. As a further step, we want to explicitly model typical marketing strategies, defining software vendors as independent actors in the diffusion network.

5. References

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