Determinants of Diffusion in Network Effect Markets

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ABSTRACT

While economic theory of positive *network externalities* is focussing rather on the *installed base* of a given product than on structural properties of the *personal* network which influences the individuals' decisions, geographical and sociological network analysis covers many structural properties but does not adequately model the dynamics of diffusion processes itself when strong externalities exist. Our paper integrates both approaches into a simulation model of the actual diffusion process and identifies determinants predicting its result. While heterogeneity of preferences, high product prices and a decentralized, regional or sparse structure of the network prevent concentration, homogeneous preferences, low prices, high connectivity, a random "global" topology or a centralized structure of the network promote concentration towards a single product.

1 Introduction

The market of information and communication technology (ICT) is critical important for the world economy. It is growing 27% faster than the overall worldwide economy and generated $1,800 billion in spending in 1997 (WITSA 1998). Daily success stories of young companies with skyrocketing stocks and new emerging innovations that penetrate the market within months (the new Internet standard XML is a good example) illustrate the dynamics and innovativeness. The question arises what specific characteristics distinguish these markets from others and whether existing models from fields like economics or information systems are able to explain it's specific phenomena.

Economic literature commonly agrees that the ICT markets are significantly influenced by so-called positive network effects, i.e. the willingness to adopt a product innovation positively correlates with the number of existing adopters. These effects mainly originate from two different areas, the need for compatible products to exchange data or information (*direct network effects*) and the need for complementary products and services (*indirect network effects*) (Katz/Shapiro 1985, Economides 1996). Since the early approaches of analyzing demand-side interdependencies in the telecommunication market (Rohlfs 1974, Oren/Smith 1981), there has been a broad discussion of positive network effects in economic literature. But taking a closer look at the existing approaches, they seem insufficient to explain important phenomena of today's ICT markets such as:

- the coexistence of different products despite strong network effects,
- the appearance of small but stable clusters of users of a certain solution despite the fact that the competition dominates the rest of the market,

- the fact that strong players in communication networks force other participants to use a certain solution

Aiming at better explanation of real world phenomena and in order to encourage further research in this field, we develop a framework for the diffusion of innovations in network effect markets. Our main hypothesis is that diffusion processes in information and communication markets are significantly influenced by personal communication relationships of the potential consumers and that a number of structural network determinants can be identified which explain the phenomenological variety of diffusion courses. In the following section we will give a short overview of existing approaches of network effect theory, diffusion analysis, and network analysis. In section 3, we will systematically identify determinants of diffusion processes in the ICT market which will be evaluated by simulations in section 4 and 5. Finally, we will discuss further research in section 6.

2 Literature Review

Within the *theory of positive network effects*, various perspectives can be distinguished (Kleinemeyer 1998, Yang 1997). Looking at *empirical* approaches authors mainly try to prove the existence of network effects and estimate their values by using regression analysis to estimate the hedonic price function of network effect goods (Hartmann/Teece 1990, Gandal 1994, Economides/Himmelberg 1995, Moch 1995, Gröhn 1999). Theoretical approaches such as Rohlfs 1974, Oren/Smith 1981, Katz/Shapiro 1985, 1986, and 1994, Farrell/Saloner 1985 and 1986, Arthur 1989, Besen/Farell 1994, and Liebowitz/Margolis 1995 mostly use equilibrium analysis to explain phenomena such as the start-up problem, market failure, instability (also called "tippiness"), and path dependency in network effect markets. Taking a closer look, the models are not sufficient to cover real world diversity for various reasons. The examination of network effects in markets is done in a rather general way. The simple distinction between direct and indirect network effects alone is not detailed enough for an analysis of demand behavior in ICT markets. In contrast to the real world where communication within the individual communication network is a very important issue, direct network effects are considered in the utility function of individual consumers only as the aggregated number of users in a market (installed base).

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 (Weiber 1993). 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 (for a comprehensive overview of the traditional diffusion models refer to Mahajan et al. 1990). Probably most famous is the *Bass model*, which has been used for forecasting innovation diffusion in various areas such as retail service, industrial technology, agricultural, educational, pharmaceutical, and consumer durable goods markets (Bass 1969). Despite the existence of various diffusion models, the approaches are not sufficient to model the diffusion of network effect products. Schoder names various areas of deficits (Schoder 1995, 46-50). First of all, there is a lack of analysis concerning the phenomenon of critical mass and lock-in effects. Furthermore, the traditional diffusion models are not able to explain the phenomenological variety of diffusion courses. Additionally, the models do not sufficiently consider the interaction of potential adopters within their individual socio-economical environment (e.g. adoption behavior within certain groups).

Diffusion models can also be found in the field of *network analysis* from various disciplines like sociology (e.g. Jansen 1999), and geography (e.g. Kansky 1963, Hagget et al. 1977). We will analyze some of them in the next section, since they seem promising for our research objective.

3 Determinants of Diffusion Processes in Networks

The main benefits of information and communication technology derive from the ability to exchange data or information between system components. Users can be seen as participants of communication networks within which it is fundamental that communication partners use compatible standards and therefor coordinate the use of their individual technology (Buxmann et al. 1999). Unlike most of the existing models for markets with network effects, we want to conduct simulations by modeling the information and communication technology 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.

For the identification of structural determinants of diffusion in networks we will use sociological and geographical concepts from a research field called *relational network models of the diffusion of innovations* (Valente 1995). The latter analyzes how direct contacts between participants of networks influence the decision to adopt or not adopt an innovation. The basic concept is the *personal network exposure* which is a measure of how intensively an individual is exposed to an innovation, i.e. how many of his or her links directly lead to an adopter of a certain innovation. This is exactly the basic assumption of positive network externalities, i.e. the likelihood of adoption gets higher with increasing personal network exposure. We will consider this in our model of the individual buying decision.

Network effects lead to intra-group pressure towards conformity, which has been proven for business networks by empirical studies (Westarp et al. 1999) and is analyzed in the literature by the concept of *group membership*. This determinant is especially relevant for innovations that are highly interdependent such as electronic communications (Rice et al. 1990). Groups or clusters within a larger network are typically identified by a higher intra-group communication density or degree of interconnectedness (Richards 1995). Another result of high intra-group density is that the group and it's participants are more resistant against influence from outside the own restricted set of communication partners (Dankowski 1986). This is an explanation for the phenomenon that even in networks with very strong network effects, such as EDI networks, we find various stable clusters of certain standards (Westarp et al. 1999). This effect of course fades the higher the density of the whole network gets, since clusters converge to one large group of highly interconnected participants with high overall social pressure of standardization.

Besides the collective pressure towards compatibility, some individual participants in networks might have strong influence on the adoption decision of many others. The concept of *opinion leadership* analyzes this constellation. The extraordinary status of opinion leaders can result from different circumstances. On the one hand side an actor might influence others by power. Case studies show that companies are often urged by important business partners to buy compatible communication systems (Trunda/Westarp 1998). Additionally, opinion leadership can also be the result of a high number of nominations, i.e. incoming direct links from other participants, or, taking also indirect links into account, of a high centrality. This means that a central participant reaches others easier, that is the number of links (distance) to others in the network is smaller. In the literature, various centrality measures exist for individuals and for the whole network (Freeman 1979, Bolland 1988).

DETERMINANTS	PARAMETERS
costs	price
stand alone utility (functionality) of the products	heterogeneity of preferences
influence of communication partners	function of network effects
personal network exposure	number of direct links to adopters
intra-group pressure towards conformity	intra-group density, network topology
opinion leadership (power)	extent of influence (network effect on other participants)
opinion leadership (location)	centrality
intensity of communication	connectivity

Table 1. Determinants of diffusion of innovations in networks.

Table 1 summarizes the structural determinants of the diffusion of innovation in network effect markets and the parameters that will be used for the simulations.

4 Simulation Design

Basis of our simulation is a simple model of the individual buying decision in network effect markets. A participant buys a certain network effect product whenever the benefits (sum of stand-alone benefits and network effect benefit; the latter depends on the number of other adopters that are directly linked to this participant) are larger than the costs. In case of competing products in a market, the consumer buys the product with the maximum surplus if this exceeds 0. Only one product is used at the same time (this is a common assumption in many network effect models, e.g. Wiese 1990, 10).

All 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 networks had a size of 1,000 consumers. We also tested our simulations for other network sizes without significant difference in the general results. A total number of 10,000 independent simulations were run until an equilibrium was reached. To analyze the diffusion process the distribution of products reached in this equilibrium was then condensed into the Herfindahl[1] index used in industrial economics to measure market concentration (e.g. Tirole 1993). In the following diagrams, every small circle represents one observation.

All entities of our model were implemented in JAVA 1.1 and their behavior was simulated on a discrete event basis.

[1] 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*(0.1)^2 = 0.1 while we get a maximal concentration index of 1*1^2+9*0^2 = 1 if the diffusion process converges to all consumers using one identical software product.

Network Structure

At first, the n consumers are randomly distributed 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 according to the parameters *connectivity*, *closeness*, and *centrality*. These parameter are introduced to analyze the central hypothesis of our paper, namely: Ceteris paribus (e.g. for the same network *size*) the *specific* neighborhood structure of the network strongly influences the diffusion processes. In the following, we will introduce the parameters.

- *connectivity* $\in \{1;2;...;20\}$: The discrete number of direct neighbors attributed to each node (identical for all 1000 consumers).

- *closeness* $\in [0;1]$: The continuous probability that a given node gets his c direct neighbors assigned to be the c consumers geographically closest to the node at stake. With the probability (1- *closeness*) the direct neighbors get randomly selected. The extreme cases, i.e. all nodes get assigned closest resp. random neighbors, are referred to as *close* topology or *random* topology, respectively.

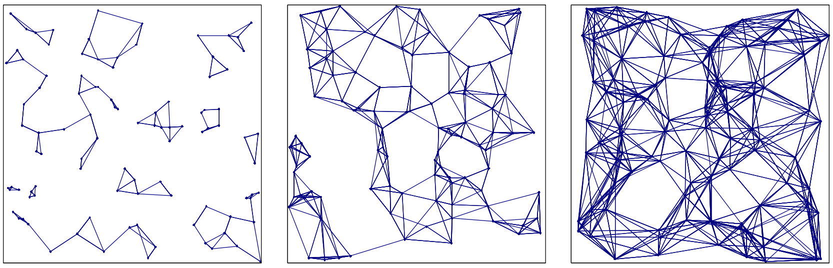

Figure 1. Typical networks with two, five or ten closest neighbors (close topology, i.e. closeness = 1.0).

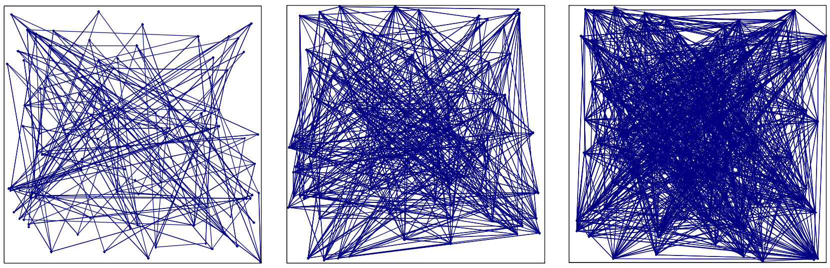

Figure 2. Typical networks with two, five or ten random neighbors (random topology, i.e. closeness = 0.0).

The graphs in figure 1 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 cannot 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 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.

- *centrality* $\in [0;1]$: For calculating the *n* closest neighbors of node *x*, we usually sort all nodes by ascending Euclidean distance d(*x*, *y*). The centrality parameter biases this distance measure by calculating a weighted sum of the two nodes' Euclidean distance d(*x*, *y*) and the Euclidean distance d(*y*, *center*) of the target node y to the geographical center (0.5; 0.5) of the unit square on which the nodes are plotted. The parameter *centrality* weights the two terms[2]. If it is zero no "penalty" for off-center nodes is considered and direct neighbors are selected only based on local distance. However, when centrality is one, all *c* neighbors are selected to be the *c* most central one, fully ignoring the own distance to this node. In this extreme case every node (except for the *c* central nodes themselves) selects the same direct neighbors, yielding their

[2] This yields $(1-centrality)*d(x,y)+centrality*d(y,center)$ as the total term of our fictitious distance measure by which the list is sorted.

"central role" as *opinion leaders*. Figure 3 shows how the parameter *centrality* influences the network topology.

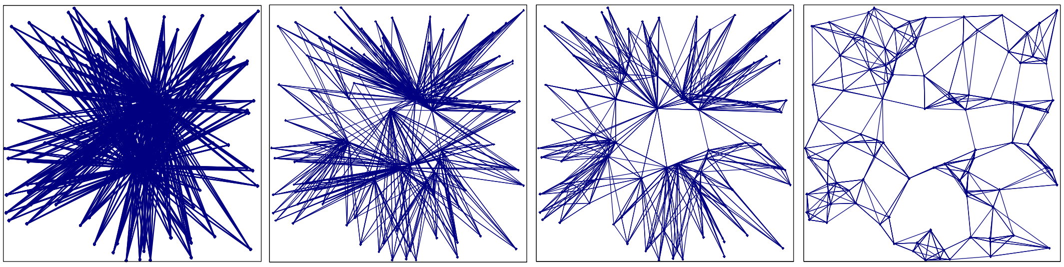

Figure 3. The effect of the centrality parameter on close topology graphs (100%, 75%, 50%, 25%).

Preferences, Prices, and Network Effects

Regardless of topology, in our simulation, every consumer can choose from all existing products and knows all their prices. Initially, all consumers are (randomly) equipped with one product, which may be considered to be their initial endowment that 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;4000].

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

In order to isolate the network's structural properties from other effects, we also decided to fix all prices for the 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*.

Dynamics of the decision process

In each iteration of the diffusion, every consumer decides whether to keep her old product or whether to buy a new one based on the decision rationale described above. The old product is assumed to be discarded once a new one is bought, i.e. it can neither provide the deciding consumer with direct utility nor her 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 product their neighbors are currently using. 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.

5 Simulation Results and Conclusions

The equilibrium concentration was found to positively correlate with the two exogeneous parameters *connectivity* (0.454) and *centrality* (0.442) and negatively with the *closeness* (-0.314). Although highly significant, the correlations themselves do not look as strong as we might have expected. Let us therefore explore a graphical illustration of the dependencies:

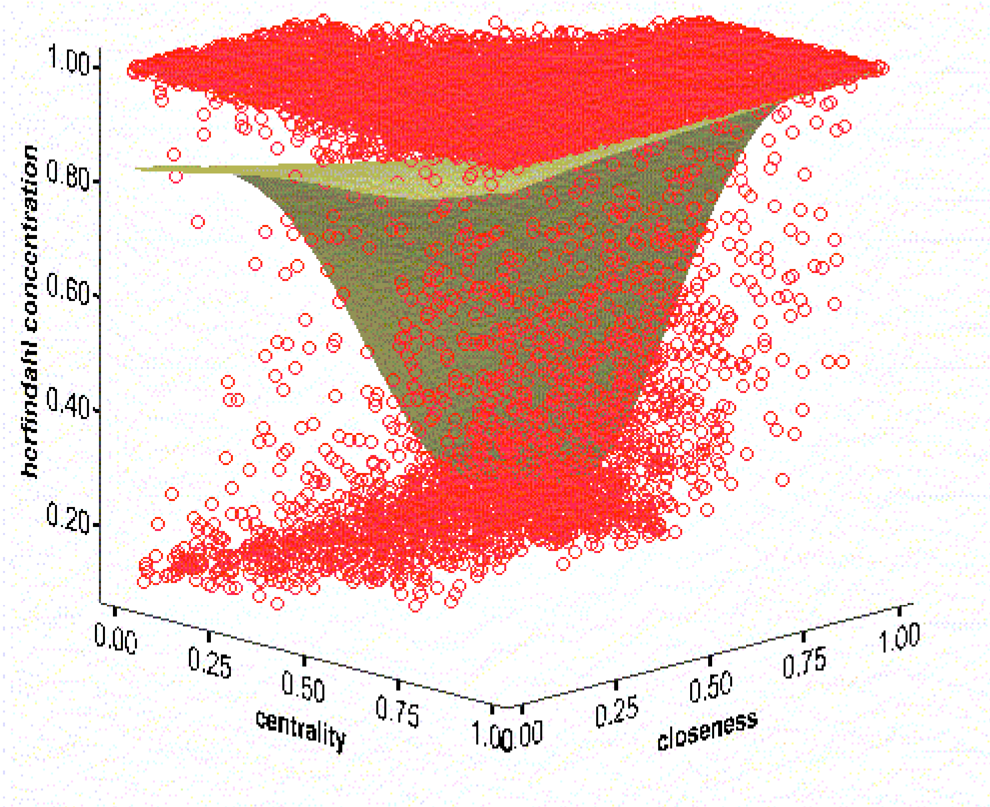

Figure 4. Joint impact of centrality and closeness on equilibrium concentration.

As we see from figure 4, for *close* topology and *low centrality* we almost certainly get low equilibrium concentration, i.e. multiple products survive, while increasing centrality or closeness fosters the concentration process. But we also see that that varying the centrality in a *random* topology (closeness = 0) has an equally low impact on the concentration as varying *closeness* in a totally *centralized* (centrality = 1) topology. This explains the low univariate correlations[3].

[3] For example, the correlation of *concentration* and *centrality* rises to 0.864, when we only consider those simulations with a closeness > 0.9.

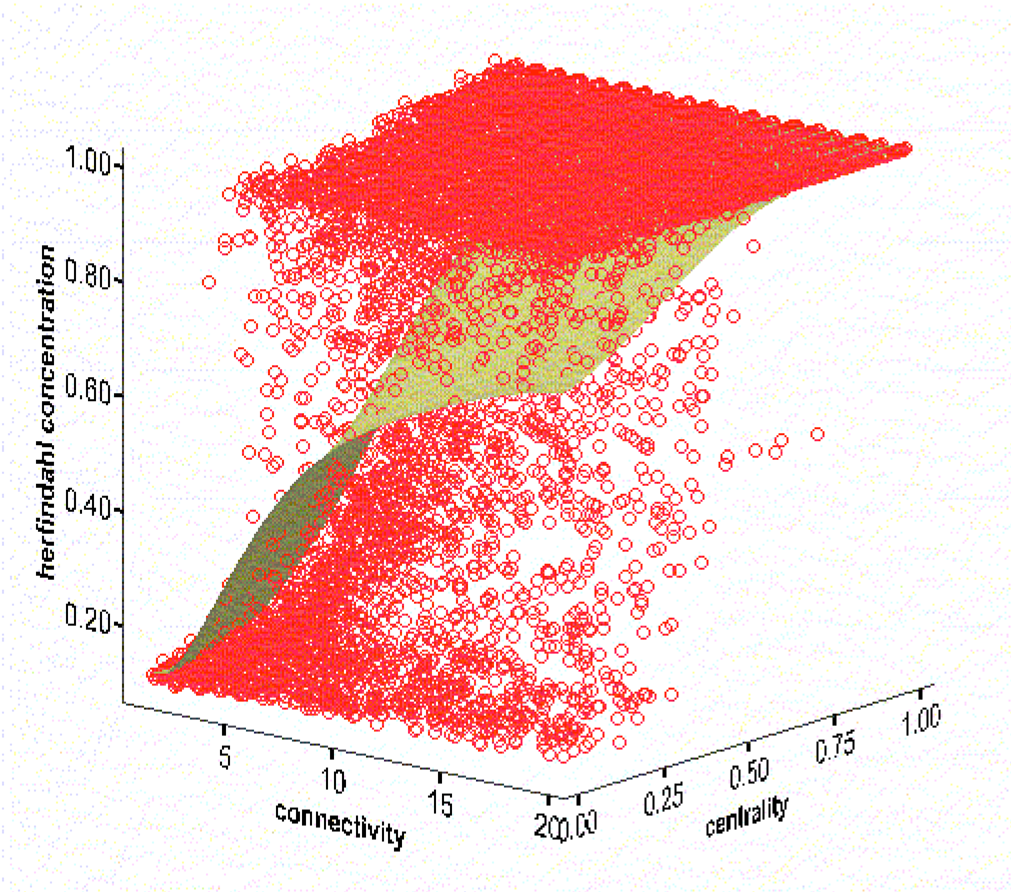

Figure 5. Joint impact of connectivity and centrality on equilibrium concentration.

For the interplay of connectivity and centrality we get a similar picture (figure 5): In networks of *high centrality* even a *low connectivity* will not prevent the diffusion process from converging to a concentrated equilibrium.

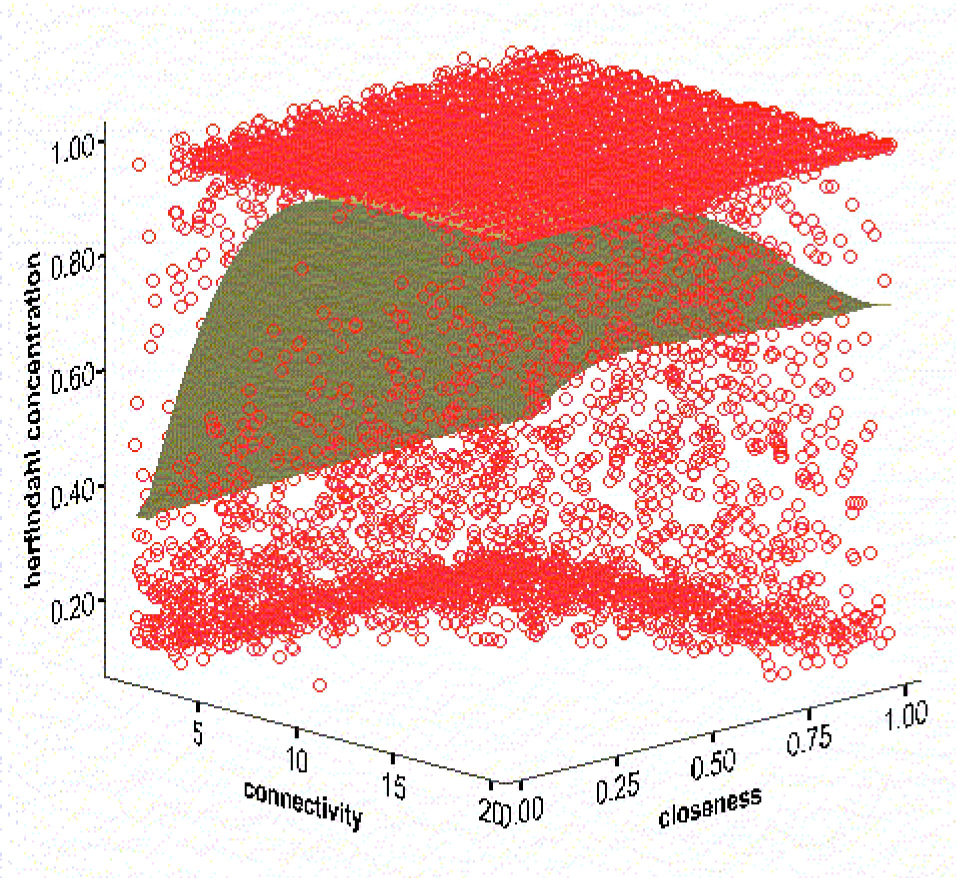

Figure 6. Joint impact of connectivity and closeness on equilibrium concentration.

For the joint effect of *connectivity* and *closeness* (figure 6), this dominance is not quite as strong as in the other two cases: Even for *random topology* networks and networks with *high connectivity* the other parameter may still have a significant impact on the concentration.

These results strongly support our main hypotheses concerning the determinants of diffusion:

- In earlier research, we analyzed the effects of *cost* and *stand alone utility* by varying price and the heterogeneity of preferences (Westarp/Wendt 2000). In high price markets we find more diversity of products, due to the higher switching costs. We did not find any significant dependency between heterogeneity and market concentration for *close topologies*, but a slight but significant negative correlation for*random topologies.*
- *Intensity of communication* (represented by *connectivity*) is the source of *personal network exposure* within the diffusion process and is shown to have a *positive* effect on equilibrium concentration.
- *Intra-group pressure* positively correlates with *closeness* of the network's topology and *closeness* is shown to *negatively* correlate with concentration[4],

[4] As a direct measure of intra-group pressure we calculated the „relative 2nd order radiality", being the sum of the number of indirect neighbors of each node divided by the hypothetical maximum of indirect neighbors (if there were no double nominations by any direct neighbor). This measure positively correlates (.405) with concentration, since a *low* value indicates strong intra-group links and thus resistance to outside pressure.

meaning that although this pressure enforces *group conformity*, it also inhibits *inter-group conformity*.

- *Opinion leadership* has been simulated by *centrality* and *heterogeneity of node sizes* (the latter was used to represent the strength of influence on others). We find a positive correlation between centrality and concentration, showing that some central participants can significantly influence the diffusion process. Differences in power within the network did not have any effect on concentration unless it was combined with centrality.
- The influence of the networks *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 clusters or groups of consumers may decide relatively independent from diffusion processes in the rest of the market), the *random* topology tends to dominance of one or few products.

6 Further Research

Despite the strong impact of *centrality* and *closeness* on the diffusion process, we are well aware of the fact that although the exogeneous parameters are sampled independently and thus do not correlate among each other, our *geographical* construction procedure is to some extent arbitrary and the two parameters *closeness* and *centrality* are parameters of this procedure rather than parameters of the resulting network *itself*. One could therefore argue that even though we "throw away" the geographical structure after having generated the neighborhood relation and do not make any use of the nodes' location during the diffusion process, our results might only be generalizable to *geographic* networks since certain neighborhood relations might never be sampled by our procedure[5].

As a possible escape from this problem we could consider shifting our focus to explore the *direct* explanatory power of *structural* characteristics of the *networks* themselves, like e.g. its *average shortest path length*, on the diffusion process. Although, there is indeed a correlation of -.643, which is stronger than the correlation of any other single parameter, this escape is only a partial one: all structural characteristics we tested systematically correlate with *closeness* and *centrality* and therefore certain combinations of these characteristics are never generated.

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[5] For example, imagine the (admittedly fictitious) case that children tend to buy silverware compatible with the one they are going to inherit from their parents: Thus the neighborhood relation is acyclic and exhibits „generation layers" having no intra-layer links at all. It is highly improbable that such a structure (or any other acyclic one) will ever be generated by our procedure.

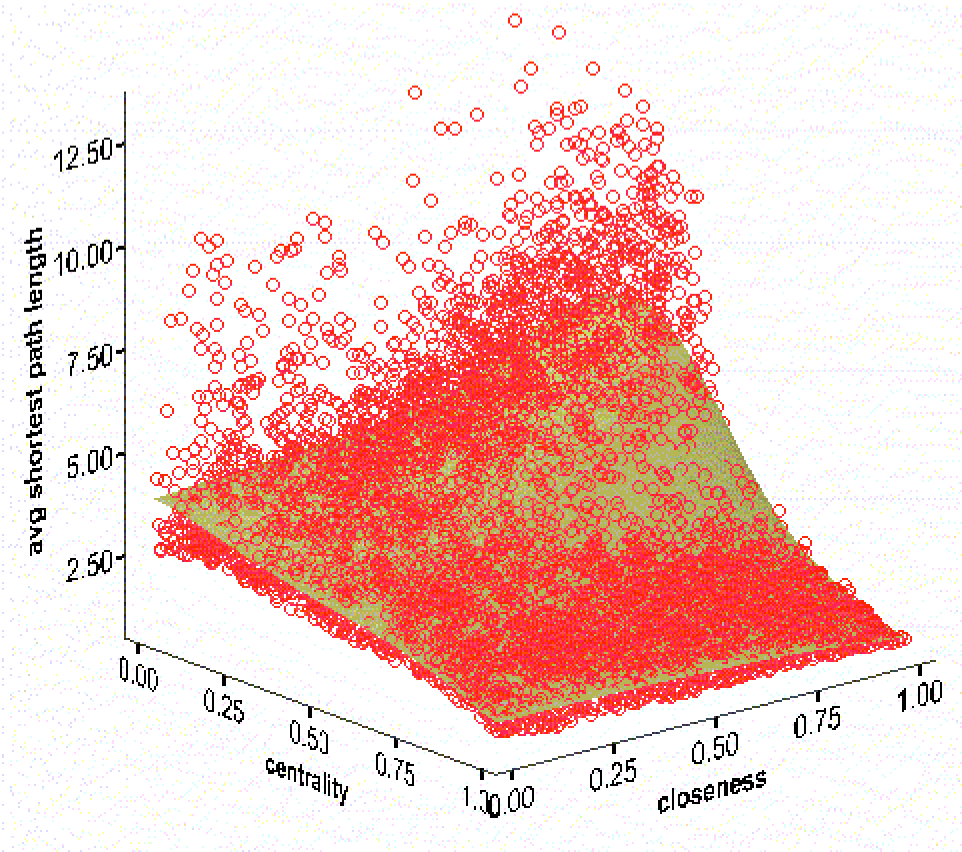

Figure 7. Joint impact of centrality and closeness on average shortest path length.

There are only two ways out of this dilemma: either collecting a large number of "real world" graphs (geographical and non-geographical) from different domains, and hoping that these samples are representative, or rather "breeding" artificial graphs matching given target combinations of characteristics[6].

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[6] Although this „breeding" is an NP-hard combinatorial optimization problem in most cases, we obtained some promising preliminary results with the application of simulated annealing (Kirkpatrick et al. 1983) .

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