Pricing in Network Effect Markets

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Abstract- **According to literature, *penetration pricing* is the dominant pricing strategy for network effect markets. In this paper we show that diffusion of products in a network effect market does not only vary with the set of pricing strategies chosen by competing vendors but also strongly depends on the *topological structure* of the customers' network. This stresses the inappropriateness of classical "installed base" models (abstracting from this structure). Our simulations show that although competitive *prices* tend to be significantly *higher* in *close* topology markets, they lead to *lower total profit* and *lower concentration* of vendors' profit in these markets**.

I. Introduction

Positive network effects (said to be existent whenever the willingness to pay for a certain product depends on the number of other users of the same product) are an important characteristic of modern information technology markets. These effects strongly influence the marketing strategies of vendors. Beside the product policy, e.g. choosing the degree of compatibility to other products, the communication policy, e.g. influencing the expectations about future success of a network effect product, the pricing strategy is most important for the success of network effect products. Generally speaking, pricing is of great importance for all stages of the product life cycle (Wiese 1990, 5-6). When introducing a product to the market suppliers must convince potential early consumers to buy although they do not experience any positive network effects yet. Typically they do so by low prices which later increase with growing market share. But even when a critical mass of users was successfully established, pricing remains a critical factor to build entry barriers against competitors since modern network effect markets tend to be very dynamic.

Pricing models of traditional network effects theory generally focus on the *installed base* of a given product, i.e. the total number of users within the whole market, as the most important factor for buying decisions. Contrary to this, we propose that the individual environment in the personal communication network of a potential consumer determines the buying decisions and must therefore be taken into account when designing appropriate pricing strategies for network effect markets.

In the remainder of this article we will first analyze existing pricing models of the network effect literature and identify existing insufficiencies (section 2). In section 3 we will present results of earlier research introducing our basic simulation model. Based on the findings we will conduct simulations of dynamic pricing strategies of competing vendors analyzing the implications of different market topologies. Concluding the paper, we will summarize our findings and give an outlook on further research.

II. Literature Review

There are various approaches in economic literature analyzing the pricing of network effect goods. Estimating the hedonic price function some authors prove the existence of network effects for products like computer hardware (Hartmann/Teece 1990), spreadsheet software (Gandal 1994, Brynjolfsson/Kemerer 1996), database software (Moch 1995, Harhoff/Moch 1996), and word processing software (Gröhn 1999) and evaluate their influence on the market price empirically. The regression analysis shows that in network effect markets the price consumers are willing to pay is significantly higher if product characteristics enable compatibility and therefore generate network effects (Gröhn 1999, 115-136).

Focussing on optimal pricing in network effect markets two strategies have been distinguished in the literature. *Personal price differentiation* means that network effect goods like software are sold to different user groups for a different price if the market allows such a separation. In the context of positive network effects the idea is to sell the product cheaper (or even giving it away for free) to consumers with a low willingness to pay (students, seniors) to increase the installed base. With growing market share and growing network effects the sales of the product increase generating revenue from the groups with a higher price, e.g. companies (Wiese 1990, Rohlfs 1979). This approach reflects the general assumption of most network effect models namely that the installed base of the whole market and not the personal network of a consumer influences the individual buying decision. Apart from the fact that today's students might become full paying customers in the future, is obvious that this assumption is unrealistic since students will rather communicate with other students and companies will rather communicate within their business networks devaluing the network effects of the respective other group. We will later show the implications of this aspect. *Dynamic pricing* is another strategy that is analyzed by many authors (Wiese 1990, Katz/Shapiro 1996, Yang 1997, Klemperer 1987a, Clarke/Darrough/Heineke 1982, Katz/Shapiro 1994). Generally, an increasing price path is proposed for network effect goods, meaning that a new product is free or sold very cheap in the beginning of its life cycle to gain an installed base big enough to overcome the start-up problem. With increasing positive network effects and therefore higher willingness to pay, in later periods the price will be raised generating sufficient revenue.

Taking the phenomenon of critical mass and the start-up problem into account these pricing strategies are analyzed for vendors in monopolistic (Wiese 1990, Yang 1997, Clarke/Darrough/Heineke 1982), or competitive environment (Wiese 1990, Katz/Shapiro 1996). Some authors also directly compare pricing strategies and its implications for different market types (monopoly, duopoly, oligopoly) (Economides/Himmelberg 1995, Wiese 1990).

Other prominent areas of interest are *pricing and licensing to competitors* (Economides 1996), *pricing and switching costs* (Klemperer 1987a, 1987b), *pricing and timing of upgrades* (Thum 1995, Yang 1997), *bundling strategies* (Bakos/Brynjolfsson 1999).

Most of the existing approaches use *equilibrium analysis* to analytically determine the results of pricing strategies in terms of market share. Network effects are considered in a rather general way, focussing only on the installed base of the whole market. The importance of personal communication networks are not taken into account which implies that the market is considered to be a completely connected graph in which every consumer is influenced by the buying decisions of every other. The more realistic assumption of bounded rationality is not modeled (every market participant knows the decisions of everyone else). However, since assuming bounded rationality usually implies the impossibility of determining analytical (ex ante) results for an aggregated entity - such as a whole network consisting of individually deciding agents - in terms of the existence and/or efficiency of equilibria, a recourse to empirical and simulative approaches seems unavoidable. Wiese (1990) criticizes the simplifications of analytical models and develops a simulation model with the more realistic assumption of discrete parameters (e.g. participants, number of sold products and time) replacing the simplification of continuous parameters and marginal results of analytical models. Defining price, heterogeneity of preferences and one- or double-sided compatibility as parameters his models allow for more complexity and a more detailed analysis of pricing and other marketing strategies. While this approach can be seen as a step in the right direction, once again network effects are modeled by installed base neglecting structural determinants of the market which, as we will show in the remainder of this article, play an important role for the diffusion of network effect goods.

III. Structure Matters: Earlier Research Results

A Simulation Model

In earlier research we analyzed the impact of structural characteristics of markets (such as connectivity, centrality, and topology) on the diffusion of network effect goods. We got different results for high-price and low-price markets indicating that structural determinants might also be important for choosing the optimal pricing strategy in network effect markets. In the following we will shortly describe those parts of the simulation design and results that will be important for our further research described in the remainder of this article (for a comprehensive description see Wendt/Westarp 2000 and Westarp/Wendt 2000).

We based our simulations on a simple model of the individual buying decision in network effect markets. A participant buys a certain product exhibiting network effects whenever the benefits (sum of stand-alone benefits and network effect benefit; the latter depending on the number of other adopters that are 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 zero. The decision is discrete, meaning that it is not rational to buy or use more than one unit of the same product or even of different products. This is an assumption which especially makes sense for information goods like software or telecommunication products. The network effects in the utility function only depend on decision behavior of the direct communication network of the potential buyer. This assumption is confirmed by empirical research in the software markets (Westarp et al. 1999) and also pays tribute to the bounded rationality of real-world actors.

Network structure. The networks were generated as follows. 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]. Then the network's topology was determined by choosing a certain *connectivity* (number of connections to other consumers) and a certain *closeness*. The closeness $\in$ [0; 1] is 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 to closest resp. random neighbors, are referred to as *close* topology or *random* topology, respectively.

The graphs in figure 1 show 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.

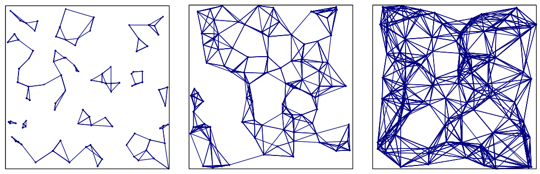


Figure 1. Typical networks with two, five or ten closest neighbors (close topology, i.e. closeness = 1.0).

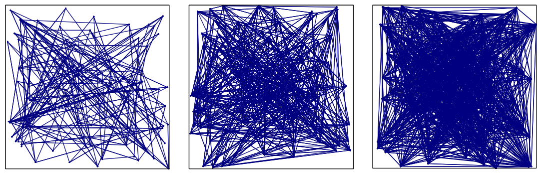


Figure 2. Typical networks with two, five or ten random neighbors (random topology, i.e. closeness = 0.0).

The standardization processes in individual clusters cannot diffuse to any consumer of a different cluster. These "subpopulations" 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.

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 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 network effects 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 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 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.

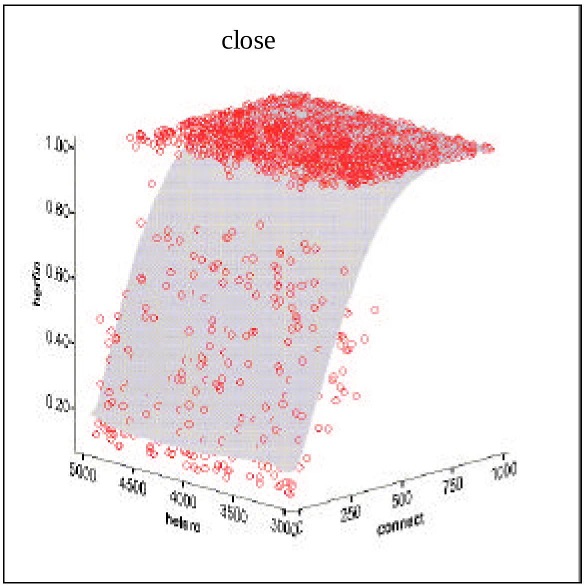
A total number of 6,000 independent simulations were run (3,000 for low-price and high-price markets, respectively) with 1,000 consumers and 10 different products until an equilibrium was reached. We also tested our simulations for other network sizes without significant difference in the general results. The distribution 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.

B Diffusion in Low-price and High-price Markets

Prices were fixed to the same constant value for all products. For the **low-price markets** the price has been chosen to be $50, which means switching to another product is very cheap compared to the positive externalities from neighbors (worth $10,000) if they use the same product.

The top diagram in figure 3 illustrates the strong correlation (0.756) of connectivity and equilibrium concentration for *close topology* in low-price markets. 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 3, 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.

The scale of connectivity is extremely different in the two graphs of figure 3. It is scaled from 1 to 10 neighbors in the bottom diagram (random topology). 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. It is obvious that in comparison to close topology markets the likelihood for total diffusion of only one product is very high in random topology networks even for very low connectivity.



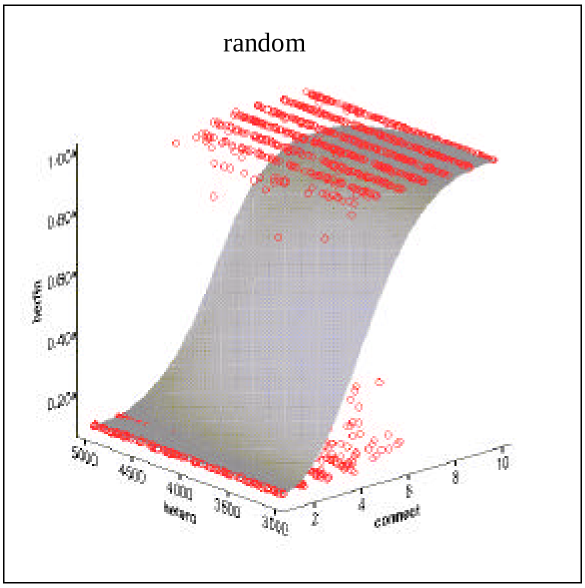


Figure 3. Equilibria in close topology and random topology networks for low-price markets.

We also considered the *heterogeneity of preferences* in the analysis as a third dimension. We did not find any significant

[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.

dependency of the sampled equilibria on this factor for *close topologies* (figure 3, top) and a slight but significant negative correlation for *random topologies* (-0.141) (figure 3, 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 (Hartung 1989, 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.

While the low-price model may be correct for competing shareware e-mail tools, or free internet-based phone or meeting software, for many other network effect products the ratio of price towards positive network externalities is less extreme. Therefor, we also conducted simulations in **high-price markets**. 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. 4) supports this rationale when we compare our results to the processes obtained for low price software (fig. 3). Note, that in the bottom graph of figure 4 the x-axis only scales up to 100 neighbors.

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.

Another very interesting effect can be observed if we additionally consider *heterogeneity of preferences*. In contrast to figure 3, 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.

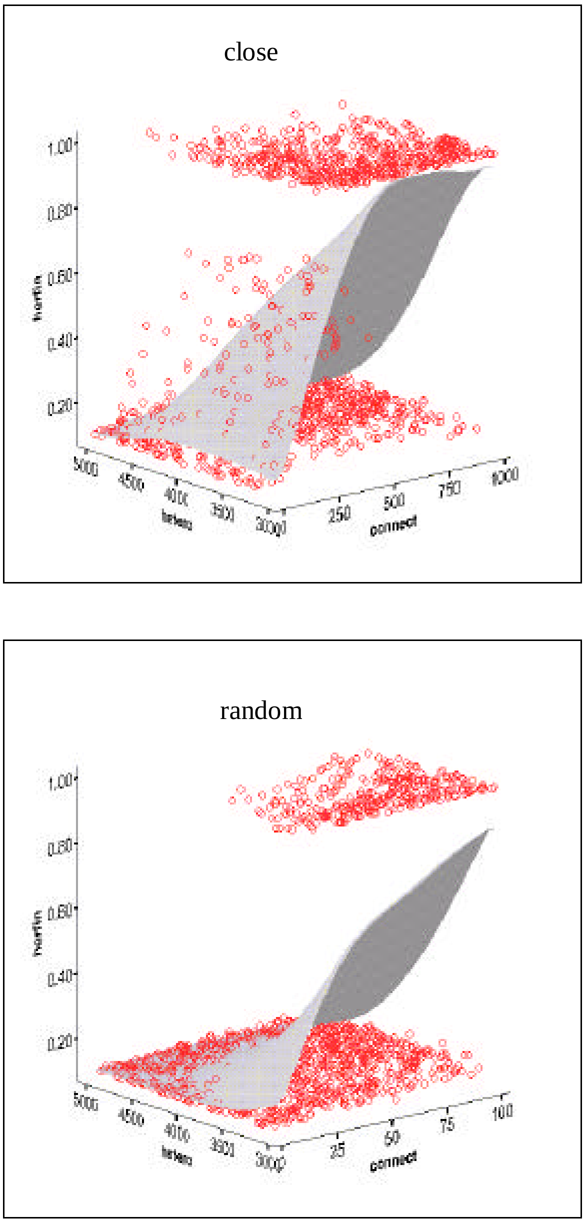


Figure 4. Equilibria in close and random topology networks for high-price markets.

IV. Simulation of Pricing Strategies

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.

Up to now all prices got fixed once, identical for all vendors and kept constant over all periods of the diffusion process. In this section of the paper we will now relax this assumption and explore the interplay of diffusion processes and pricing strategies of the vendors.

A Simulation Design

For reasons of computing time we restricted the length of the diffusion process (which was twenty) to five periods, not really posing a restriction since most diffusion processes reached an equilibrium earlier than period five.

Our ten vendors are assumed not being able to directly observe the prices of their competitors but only the *reaction* of the customers, reacting to their own pricing strategy by comparing the price and benefits of their products to those of their competitors.

In the sequel, a *pricing strategy* is considered to be a vector of five discrete integer prices, one for each period, not restricted to be positive, since we do not want to exclude the possibility to subsidize the use of a product in an early period (i.e. investing in a higher installed base) in order to "skim" the revenue from followers in later periods.

For every set of ten price strategies we obtain a specific diffusion process of a given network and thus a specific revenue (being equal to profit since we do not consider any cost at the vendors' side) for a given network topology for a given initial endowment and a specific order of decisions.

As before, we sample a topology and initial endowment and run the diffusion process (for 1000 customers with connectivity of 10, centrality fixed to zero), but not only once as before but 10,000 times with different pricing strategies, allowing the vendors to "learn how the market behaves" in response to their strategies and of course trying to find the strategy that maximizes their individual profit accounted for over the five periods.

At the start of the "pricing battle" all vendor have a constant price of 100 for each of the five periods. In the first simulated diffusion process this set of strategies yields a vector of 10 total profits. In each of the 10,000 diffusion runs another vendor gets the chance to adapt her pricing strategy in order to increase profit (in most cases at cost of other vendors). This chance is taken by simply adding a random vector of five price "deltas" (drawn from a normal distribution of mean zero and variance) to the old strategy and then testing the new strategy by simulating a diffusion. Whenever the new strategy outperforms the old one or yields the same profit, the old strategy gets replaced by the new one, otherwise the old one is kept and modified with another delta vector when it is this vendor's turn again.

Since all vendors exhibit this behavior, we might expect the "price battle" to lead to a Nash equilibrium, i.e. a set of price strategies, which makes it impossible for any vendor to improve his own profit when all other vendors stick their current strategy. Unfortunately, although many battles reached an equilibrium in the sense that no vendor successfully tried to modify his strategy for some thousands of iterations, this does not mean that this equilibrium is a Nash equilibrium, since there still might be a delta vector we just didn't sample yet and we can neither enumerate all possibilities nor analytically prove that there cannot exist such a superior strategy, since our diffusion process may itself only be simulated. On the other hand, it might be possible to establish theorems, proving that under specific circumstances the negative effects of rising or lowering a price x in an early period may not be compensated by any adaption of prices in a later period thus showing that x is part of a Nash equilibrium if (and only if) we can prove the same for all prices of consecutive periods (and all other vendors).

Nevertheless, the following figures, once again, show that the equlibria resulting from this collective learning process leads to pricing strategies which again (indirectly) depend on the network's structure, influencing the customers' reaction to a given set of price strategies.

B Results

We see from figure 5 that the total cumulated profit over all vendors (almost linearly with a correlation of -0.67) falls with the chosen closeness of the customers’ network topology while, as expected, this total profit concentrates on less vendors in random topology markets than it does in close topology markets where many vendors survive with a substantial market share. Once again, the Herfindahl index was used to illustrate this concentration (c.f. figure 6).

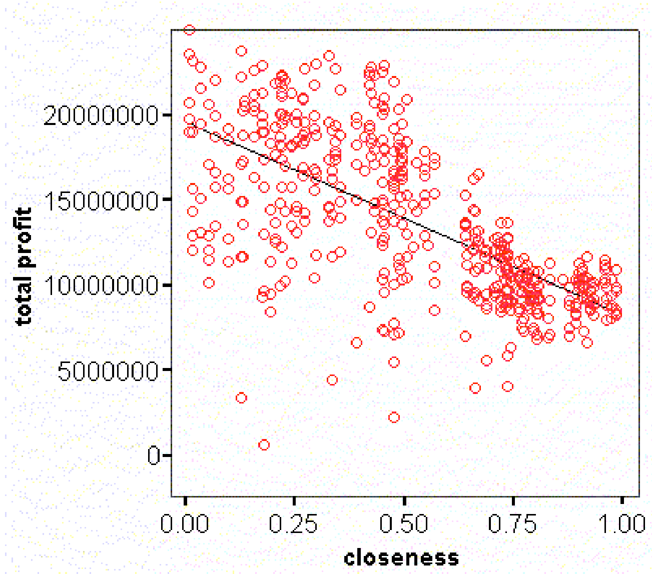


Figure 5. Summed total profit of all 10 vendors.

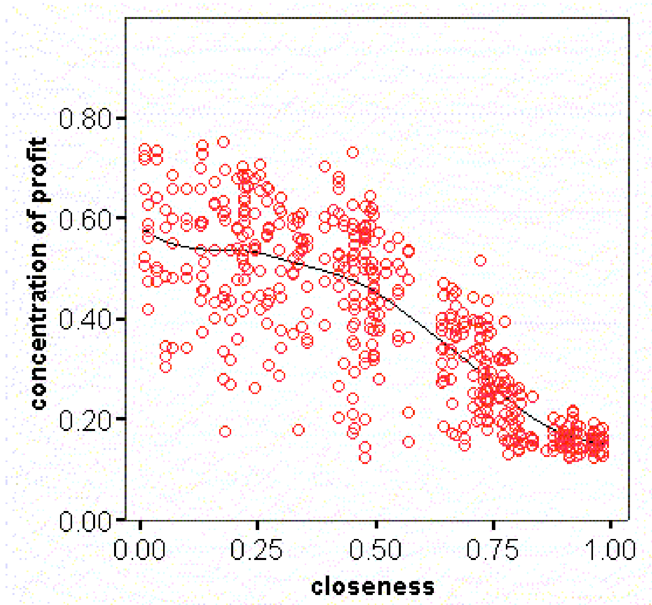
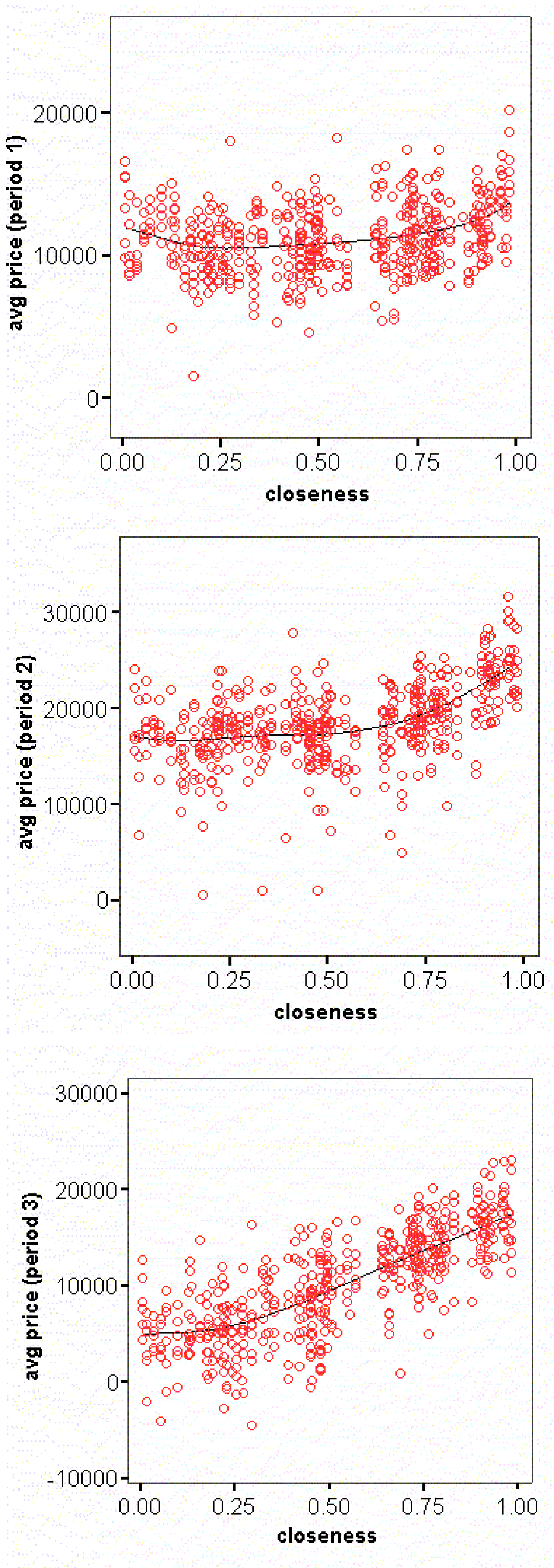


Figure 6. Concentration of total profit.

Although we might expect this to result from lower equilibrium prices in close topology markets, the following set of price charts (one for each of the five periods) clearly refutes this hypothesis: For all five periods the price *positively* correlates with topological closeness (with correlations of 0.23, 0.46, 0.76, 0.78 and 0.77 respectively).



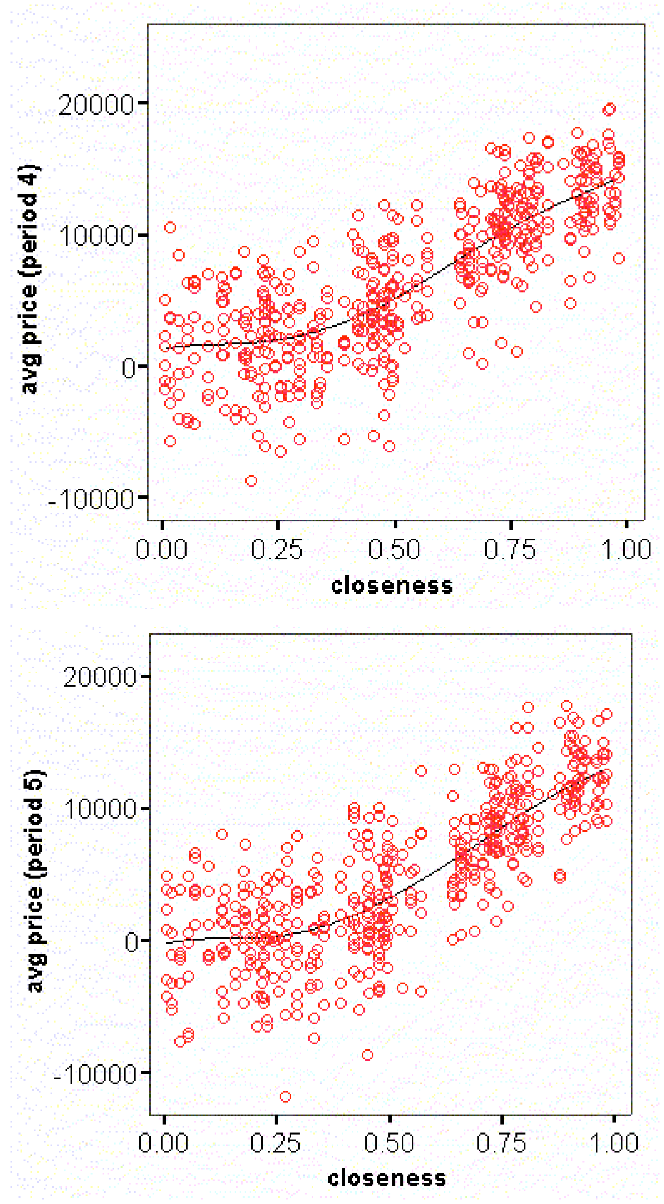


Figure 7. Average equilibrium prices for different periods of the diffusion process.

Of course, if profits fall despite increases in prices, the answer lies in the *number* of customers buying the product: In close topology markets most customers only buy a product once, leading to stable clusters of local standards, while in the more “global” markets with random topology the first choice made to align the own endowment with ones neighbors turns out to be erroneous, forcing me (and my neighbors) to buy a new product in a subsequent period (like most owners of beta VCRs finally bought a VHS recorder too and owners of WordPerfect bought MS Word). Therefore, in a close topology market, vendors have the chance to behave like “local monopolists”, each of them having their stable groups of customers crystallizing, but in most cases only have one chance to charge them. On the other hand, in random topologies there is a higher potential of selling, but also higher competition and thus the danger of losing at least those “follow up” sales to the competitor having turned out to be the standard in a later period. But nevertheless, also those vendors “loosing the battle” may derive a substantial share of total profit from the “wrong” initial decisions, which explains why even for random topologies the average concentration of total profit (over all periods) is only 0.6 although the market is taken over completely by one product and thus the concentration measured by number of users is 1.0 in those random topology cases.

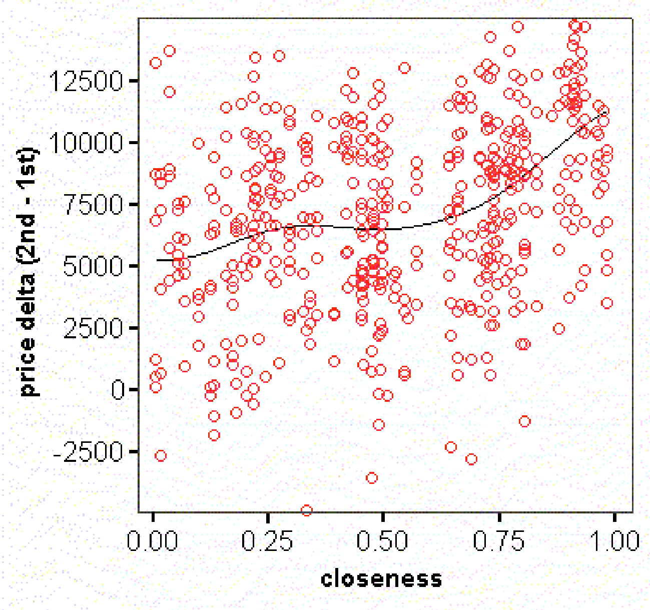


Figure 8. Concentration of total profit.

As we see from the first two charts in figure 7 and figure 8 (the latter explicitly shows the price difference between the first two periods) *penetration* pricing indeed turns out to be the dominant strategy for all vendors, no matter whether the topology is close or random. But interestingly enough, although we started each “battle” with an initial prices of 100, the vendors collectively (but without any chance for collusion!) rose this price up to a much higher level of about 10,000. This is exactly the utility drawn from a neighboring consumer using the same product. Why this is a critical value gets clear when we imagine a customer currently using product A and having e.g. three neighbors using the same product but four using product B (the remaining three neighbors using one or more other products): As long as the price of B is smaller than 10,000 the customer will be better off buying the new product, otherwise it will stick to A. Therefore, offering a price slightly below this threshold may in fact speed up diffusion of a product. That the average prices lie above the threshold is explained by the fact that once a vendor has to fight a competitor with a penetration strategy, it might turn out to be rational rather to “give up” the fight and rather select a skimming strategy by charging a higher price in the first period(s).

We also notice that after period 2 equilibrium prices fall again. That they may even fall below zero seems completely irrational for period five, since there is no future period in which such a subsidization could pay off. But since price changes get accepted as long as they yield the same (or a higher) profit, the vendors do not “notice” this, as long as there is no customer actually switching to their product and thus “asking” for the subsidy, i.e. this can only happen when diffusion has reached an equilibrium in an earlier period.

V. Conclusion and Future Research

Our simulations have proven that diffusion of products in a network effect market does not only vary with the set of pricing strategies chosen by competing vendors but also strongly depends on the topological structure of the customers' network. This stresses the inappropriateness of "installed base" models (abstracting from the??? topological structure). Although competitive *prices* tend to be significantly *higher* in *close* topology markets, they lead to *lower total profit* and *lower concentration* of profit for these markets.

Despite these interesting results many open questions remain. Our ongoing research mainly concentrates on answering the following:

- How can a given solution be proven to be a Nash equilibrium ?
- How do the strategies of (ex post) "winners" of the competition game differ from those of "losers" and what may the "losers" learn form this? (Simply copying the winners' strategy cannot make the losers better off since if it did, their current strategy would not be an equilibrium.)
- Of course, optimizing one's individual pricing strategy by this type of "learning by simulating the market and simulating the competitors" may heavily depend on how well the customer's decision model reflects their real decision function and thus we may not derive a direct recommendation for pricing a product since it might be better to run a less profitable pricing strategies which is more *robust* to variation in customer's behavior. This robustness will also be evaluated in future simulations.

Acknowledgments

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