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## Diffusion and competition of innovative cardiological technologies

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# JENA ECONOMIC RESEARCH PAPERS



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## **Diffusion and Competition of Innovative Cardiological Technologies**

by

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# Diffusion and Competition of Innovative Cardiological Technologies

Thomas Grebel\*, Tom Wilfer†

November 8, 2007

## Abstract

The paper aims to investigate the diffusion process of two competing innovative technologies in the health care sector. Novelties in cardiovascular surgery will serve as an example. Using a rather simple modeling approach for the decisions of adopters and suppliers we simulate the evolution of a new market and discuss the effects network externalities and individual learning unfold in different scenarios. Increasing returns to adoption may lead to situations of technological "lock in".

**Keywords:** technological change, diffusion processes, competing technologies, adoption decisions, social learning, medical equipment, network externalities.

**JEL-Classification:** O33, I11, D43.

## 1 Introduction

Within a research project at the Friedrich-Schiller-University Jena the introduction of new cardiovascular treatments for diseased aortic valves is analyzed. The diffusion of innovative medical technologies is a promising field of research. However some characteristics of the health care sector – such as complicated certification procedures for new technologies or highly regulated reimbursement rules – and their effects on innovation and diffusion as well as the question how cost reduction and growth effects of new technologies contribute to soaring health care costs deserve special attention. In this paper we restrict our focus on the evolution of a market segment where two innovative technologies compete for market shares. By applying a simple model of adopter

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and supplier behaviour to different scenarios and market entering strategies we develop situations where network economies lead to significant deviations from the neoclassical duopoly theory.

In section 2 of this paper we present the relevant literature on diffusion and network externalities before we discuss the properties of our example and its particular effects on diffusion in section 3. Section 4 comprises the specifications of our model and in section 5 the simulation runs for different scenarios are presented. Section 6 concludes and gives an outlook for further research.

## 2 Diffusion and Network Economies

The focus of our research interest is to explore the diffusion of novel technologies in a fallible market such as the market for health care products. Considering two new technologies, or two new products for simplicity, a static perspective, neglecting the time-consuming process of diffusion, is given by standard textbook oligopoly models. Cournot, Bertrand and Stackelberg deliver a *game-theoretic approach* about the *market-structure* and *equilibrium* of two competing (*homogeneous*) products. With a non-cooperative behavior firms compete on *quantities* (Cournot) or *price* (Bertrand). Assuming a strong *market power* of a dominant firm, that firm comes first with its decisions inducing consequential actions by a following firm (Stackelberg).

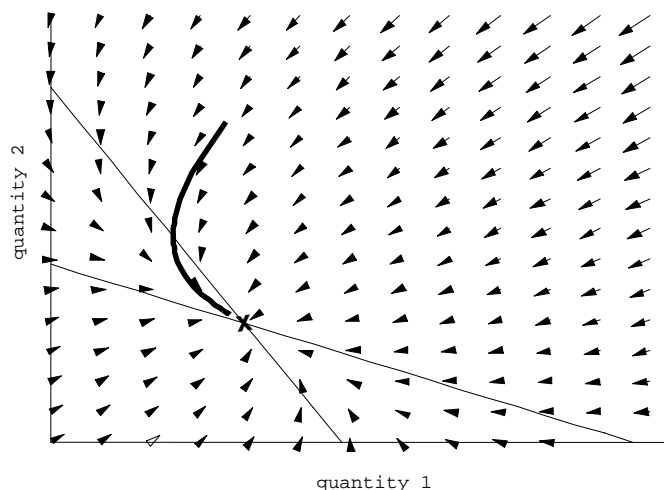


Figure 1: Resulting market dynamics and market structure with Cournot-competition.

Figure 1 illustrates an example of a Cournot-model. The intersection point (marked

with a cross) of the reaction function of two firms depicts the equilibrium point of non-cooperative duopolistic competition; market shares are equally distributed between those two firms. Modeling the firms' adaptive behavior (output to produce) with differential equations in order to show the dynamics of the market shares, the arrows in figure 1 indicate the directions and the curved line shows an exemplary dynamics.

However, the underlying assumption is that two established firms produce and sell a homogeneous product in a market of consumers with homogeneous preferences. The time-consuming aspect of diffusion, lock-in effects caused by network externalities and heterogeneous preferences are not accounted for. Those issues are discussed in the literature on diffusion. There, questions are asked such as what makes potential users adopt new technologies, what path the diffusion process takes, and what the basic drivers of the diffusion process are (Silverberg et al. 1998). Griliches (1957) came first to put an economic perspective on the diffusion of technology and explored the diffusion of hybrid corn technology across the United states. Nasbeth and Ray (1974) provide an international study on the diffusion of industrial processes. Similarly Stoneman (1976, 1983, 1987) wondered why the diffusion of technology is not instantaneous. If a new technology is advantageous, it should spread instantaneously. Evidently, the availability of the information about such a new technology is necessary. If there is a lack of information, a technology will not be adopted (Mansfield 1968). Aside from that, it is also the user's utility which decides over adoption. The consumer's utility may increase with the increasing number of users of a new technology (direct network externality) and the increasing importance of a new technology may additionally spur the innovation of complementary products (indirect network externalities), a reinforcement effect that accelerates the rate of diffusion (Katz and Shapiro 1986). Young (2005, 2007) puts his focus on the different causes of typical S-shaped diffusion curves and shows that they can be distinguished by comparing their respective acceleration patterns. Apart from empirical studies and theoretical concepts there is also a pool of models on technology diffusion.<sup>1</sup>

In the following section we develop a multi-agent model meant to substantiate the diffusion of two technologies focusing on the spread of information about a new technology within a particular social network through professional contacts<sup>2</sup>. Since social learning will be the driving force of the adoption process in our model some conceptual ideas are derived from Young (2005, 2007). Further ideas were taken from Arthur (1989)

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<sup>1</sup> Geroski (2000) gives examples and stereotypes *models of technology diffusion*. See Silverberg et al. (1998) for a further example and Metcalfe (1988) for another overview.

<sup>2</sup> Compare Narduzzo and Warglien (1996).

who provides a simple model of technology diffusion substantiating the adoption behavior according to network externalities of two competing technologies. Moreover, Meyer et al. (1996) and his heterogenous oligopoly model of two competing firms render some inspiring thoughts to model the supply side. But before we proceed to our modeling efforts, we give a short motivation of our investigated case in order to clarify why we think such an approach appears to be necessary.

### **3 Example: Percutaneous Heart-Valve Implantation**

Referring to the research project INNOHEART at the Friedrich-Schiller-University Jena we chose the introduction of a new cardiovascular treatment as an example for the investigation of the diffusion process of emerging technologies in the medical field. Aortic valves which calcify in the course of life, may face the need for replacement. The conventional way to carry out replacements of deficient aortic valves is by opening the thorax and operating on the open heart. This procedure means a comprehensive surgery with general anaesthesia and the use of a heart-lung-machine (HLM). Subsequently, it is often followed by long convalescence periods. For elderly patients, with the highest prevalence of defective aortic valves, the conventional procedure often leads to serious if not fatal complications, even more when further co-morbidities impair their condition. Therefore, a considerable share of patients remain without treatment. Evidently, this issue will get worse with respect to the expected demographic development. The innovative minimal-invasive approach to replace the aortic valve interventionally using a catheter is expected to cause much less complications. Only local anaesthesia will be required, a heart-lung-machine will normally not be necessary and the patients are expected to leave the hospital within a few days after surgery. Elderly and multimorbid patients have therefore a realistic chance to survive the replacement of the aortic valve.

For the time being this new technology is designated to open up a new market for percutaneous heart valve implantation for elderly people who cannot bear a traditional invasive treatment, but in the long run it might also compete with existing traditional treatments (technologies) where it holds considerable potential for savings. Thus apart from an improved medical treatment this technology also seems to be a cost-saving technology. The technology is currently in the pre-clinical research phase and still has to undergo time-consuming and costly certification procedures before it becomes a marketable product. Up to now, there are several competitors who work on similar projects and will enter the new market in the near future.

In our model we will focus on the evolution of a new market for the percutaneous

heart valve replacement. The aim is to describe possible paths of the diffusion of two new technologies entering the market in the health care sector. In general, health care markets are characterized by market failure. The consumer (patient) is not to a full extent able to evaluate the necessity and quality of a medical treatment. Especially in the case of heart diseases it is less the patient than the physician who determines the feasible treatment. In short, in this market we are far from perfect competition. From the supply side as well as from the demand side, actors are neither homogeneous nor perfectly informed. Suppliers do not have free access to the market as it is highly regulated. Consumers lack sovereignty in their demand; henceforth, optimizing behavior and a Pareto-efficient outcome is only by chance.

Therefore, we think a multi-agent-based model as follows to be adequate to take into account the contingencies of the diffusion of technologies in the health care sector.

### **4 Concept of the Model**

In this section the demand side and the supply side are modeled. To start with, the technology spreads through social learning among our set of potential adopters to give credit to the fact that it is the respective hospital department and its cardiologists who decide over a heart valve to be replaced, and they will thereby be influenced not only by their own attitude towards new procedures but also by the decisions and the experience of other professional experts (Narduzzo and Warglien 1996). In a social learning model the combination of both own prior attitudes towards certain innovative technologies and observed payoffs from other adopters is decisive for the adoption decision of each agent (Young 2005, 2007).

The supply side consists of two firms that produce competitive technologies. Some elements of a heterogeneous oligopoly model, as suggest by Meyer et al. (1996), will be taken and adapted to model the strategic behavior of the producers.

#### **4.1 Diffusion of Technology – Decision-Making on the Demand-Side**

The decision-making process is two-staged. First, every actor decides in general whether to adopt a new technology or not. Second, the decision for a certain supplier of the innovative technology is made on grounds of the individual preferences.

#### 4.1.1 Social Learning – Spread of Technology

Suppose we have a set of potential technology adopters  $\mathbf{N}$ . Each actor has a certain propensity  $\theta_i$  to adopt – or in other words: prior beliefs concerning – a new technology  $\mathbf{V}$ , the percutaneous heart valve implementation. Furthermore, every agent once he or she decided to adopt the new technology will benefit to a certain extent from adoption. Adopters payoff  $\mu_i$  may differ between agents due to individual differences or differing use environments. If  $A^t$  denotes the number of adopters and  $\bar{\mu}^t$  is their average payoff from adoption that can be observed by all agents in every period  $t$  the adoption rules may look as in the following:

$$V_i^t = \begin{cases} 1 & \text{if } \theta_i + A^{t-1} * \bar{\mu}^{t-1} \geq T \quad \text{or} \quad V_i^{t-1} = 1 \\ 0 & \text{if } \textit{else} \end{cases} \quad (1)$$

Actor  $a_i$ , who has not yet adopted the new technology ( $V_i^{t-1}=0$ ), will adopt the new technology if the sum of his prior beliefs ( $\theta_i$ ) and the observable payoff from the preceding period ( $A^{t-1} * \bar{\mu}^{t-1}$ ) crosses the adoption threshold  $T$ . Beside this general decision on adoption, different kinds of inertia among the agents may shape the actual adoption process as they can lead to considerable delays. We simply incorporated inertia in our model by including a parameter  $L$  which defines the share of actually adopting agents among those who changed their adoption status in Eq. (1).<sup>3</sup>

In our cardiovascular example a new procedure to replace diseased aortic valves will become available. At the latest when certification authorities approve its clinical use cardiologists start to think about using this alternative themselves. Nevertheless different cardiologists may have different expectations concerning the new technology which may let agents adopt at different points of time. Cardiologists who are familiar to the research in this field or even participated in the development of these technologies can be expected to be early adopters. Others may act with more reservation and will therefore decide not to adopt until sufficient information on the superiority of the technology is available. We account for agents' heterogeneity by attributing random numbers to the individual  $\theta_i$ , so that depending on the adoption threshold  $T$  a certain fraction  $s$  of our potential adopters  $\mathbf{N}$  serve as early adopters in  $t = 1$ . Inertia plays an important role so that resistance against new technologies or procedures may arise at different levels in hospitals. In the first place, hospital managers could restrict the use of new technologies because

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<sup>3</sup> In greater detail, we define a threshold parameter  $L$  between zero and one, before drawing pseudo-random numbers for each agent  $a_i$  who decided to adopt  $\mathbf{V}$  ( $V_i^t=1$ ). If the random number exceeds the defined threshold,  $a_i$  immediately adopts technology  $\mathbf{V}$ . Otherwise, actual adoption is postponed for at least another period since the decision process will then be repeated.



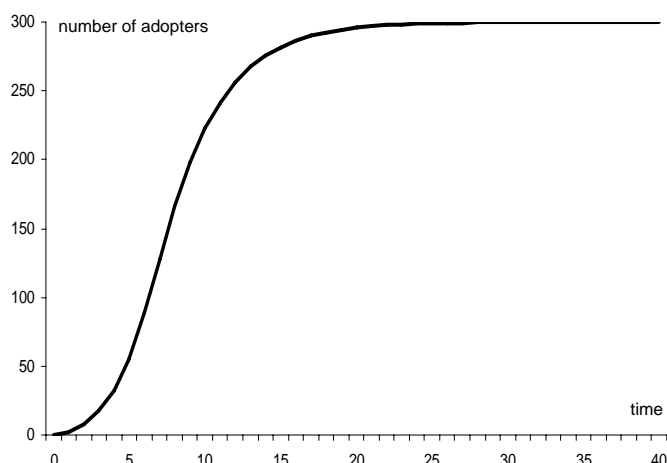


Figure 2: Diffusion process over time.

of long-term contracts with technology suppliers for alternative procedures or simply by its questionable prospects, since reimbursement regulations have yet been set up by authorities. Of special interest for our particular technology of replacing aortic valves using a minimally-invasive approach could be the reaction of cardiac surgeons as they carry out the conventional procedure and thus could find themselves in fierce competition with their colleagues from the Department of Cardiology. Hence the respective positions of cardiologists and cardiac surgeons within a hospital may be crucial for the adoption decision in our example. We assume in our model that neither patients nor single cardiologists enter the market as potential technology adopters, but rather cardiological departments in hospitals since it seems highly unlikely that the decision on technology adoption differs within the hospital entity. *Figure 2* diagrams the diffusion process over time and a typical S-shaped curve results.<sup>4</sup>

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<sup>4</sup> The parameters and initial values for the illustrated diffusion process are as follows:  $N=300$ , this number tries to represent the German market, where the number of cardiological departments was 259 in 2005 but showed a strong upward trend in recent years;  $\theta_i$  random numbers drawn from uniform distribution (range from 0 to 100);  $T=97$ ;  $\mu_i$  random numbers drawn from normal distribution with mean=0.5 and standard deviation=0.1. Inertia parameter  $L=0.75$  indicating that the probability to finally adopt  $V$  after deciding for it in Eq. (1) ( $V_i^t=1$ ) is 25 per cent for each actor. Furthermore the setting of  $\theta_i$  and  $T$  means that the share of early adopters in  $t = 1$  is around three per cent. Finally one has to point out that *Figure 2* does not reflect the results of a single simulation run, but the average values of 100 different runs to – at least partly – account for random events.

#### 4.1.2 Diffusion of Competing Technologies

In the next step we assume that the innovative technology  $V$  is offered by two suppliers,  $D$  and  $E$ . In the simplest case both versions of  $V$  have similar functions and are equal in terms of quality and price. Actors  $a_i$  who decided to adopt  $V$ , now have to choose between  $D$  and  $E$ . Since this choice is only based on a pure comparison of each actor's natural preferences  $d_i$  and  $e_i$ , the decision of adopting  $V$  and the choice for a specific supplier are clearly separated from each other. The decision rule for the choice between  $D$  and  $E$  may look as in the following:

$$D_i = \begin{cases} 1 & \text{if } d_i > e_i \\ 0 & \text{if } d_i < e_i \end{cases} \quad E_i = \begin{cases} 0 & \text{if } d_i > e_i \\ 1 & \text{if } d_i < e_i \end{cases} \quad (2)$$

with  $d_i, e_i \in [1, \rho]$

The natural preferences ( $d_i$  and  $e_i$ ) of each agent  $a_i$  are uniformly distributed random numbers. Figure 3 displays the evolution of both demand curves again as an average of 100 different simulation runs. As parameter  $\rho$  has been initialized at ten for both  $D$  and  $E$  in these simulation runs, the probability to pick either  $D$  or  $E$  was 50 per cent each. Thus both curves evolve almost completely similar over the entire time span. How can  $d_i$  and  $e_i$  be interpreted in our cardiovascular case? The natural preferences may reflect personal preferences of the respective group of cardiologists concerning the handling and usage of  $D$  or  $E$ , long-term relationships of the hospital with certain suppliers on related technological fields (indirect network externalities), preferences for national suppliers or differences in supplier behavior or service capacities for different regional markets.

#### 4.2 Decision-Making on the Supply-Side

We now introduce the decision-making processes of the suppliers of technologies  $D$  and  $E$ . In every period, firms have to decide upon two parameters: price and quantity.<sup>5</sup> We therefore include simple rules for price and quantity.

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<sup>5</sup> In equilibrium a firm could only determine one parameter because of the other being endogenous.

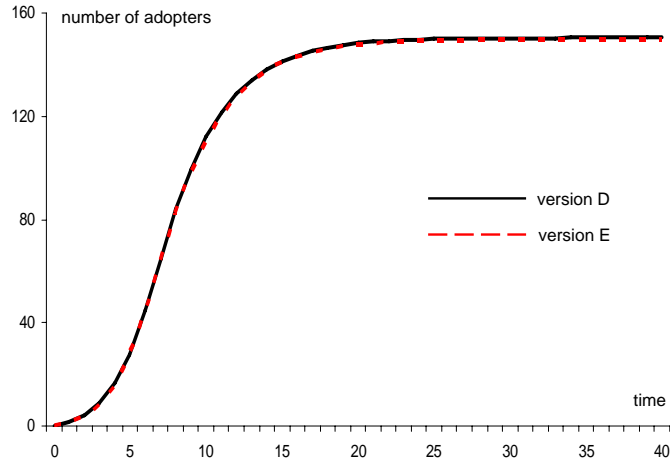


Figure 3: Diffusion of Competing Technologies.

#### 4.2.1 Pricing - Erosion, Interdependency and Reaction to Demand Surplus

The price rule looks as in the following:<sup>6</sup>

$$p_m^t = (p_m^{t-1})^\varepsilon + \alpha * (p_k^{t-1}) + \beta * \left( \sum_{i=1}^N m_i^{t-1} - X_m^{t-1} \right) \quad (3)$$

Three terms determine the market prices for **D** and **E**. The first term implies a steady decline in prices since  $\varepsilon$  is supposed to be smaller than one. Falling prices may not only result from Bertrand-like price competition in a duopoly, but may also reflect strict regulations on health care markets. The introduction of benchmarked Diagnosis-Related-Groups (DRGs), a case-based payment, in a number of industrialized countries forces actors on all levels of the health care sectors to reduce their expenses. Hospital managers, representatives of health insurance companies as well as policy makers will increasingly exert pressure on the suppliers of medical technologies. The here presumed decline in prices can also be observed for related cardiology technologies. Hence high-pricing strategies may be suitable for market entry to start the fall in prices from a higher level, but will not be optimal in the long run, since a loss of market shares would be inevitable. Marginal costs  $c$  constitute the limit at the lower end of the pricing scale.

A certain degree of oligopolistic interdependency between the two firms is taken into

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<sup>6</sup>

$m, k = \{D, E\}; m \neq k; 0 < \varepsilon < 1; \alpha, \beta > 0; p_m^t \geq c$

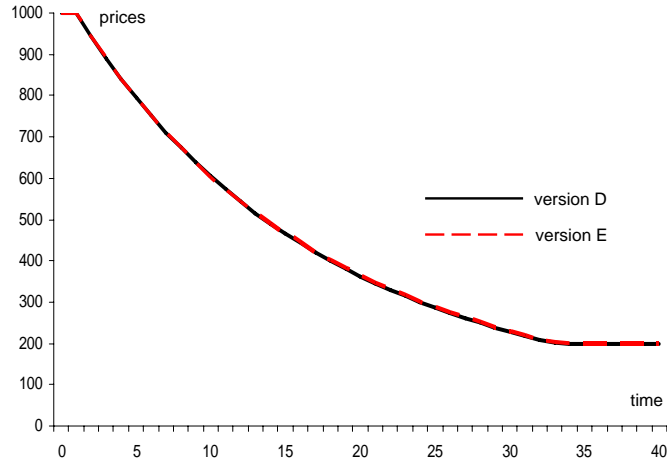


Figure 4: Price Trend - Competing Technologies.

consideration via the second term of the pricing formula. Thus a strategic component is included. High prices charged by the competitor in the preceding period lead to an increase in own prices for the current period. To which extent this impact will work depends solely on the size of parameter  $\alpha$ . The effect of a possible demand surplus in the previous period on the price setting unfolds through the last term. If the demanded amount, calculated as the sum of demand for  $D$  and  $E$  over all  $N$  individuals, exceeds the number of produced heart prostheses in the previous period, the providers will react with an increase in price. The magnitude of this effect is again dependent on the respective parameter, here  $\beta$ . Figure 4 shows the corresponding development of prices. Since initial prices, marginal costs and all other pricing parameters were identical for both versions, no differences can be observed in the course of price development.

#### 4.2.2 Quantity Setting

Decisions on the supplied quantities of  $D$  and  $E$  may be made as in the following:<sup>7</sup>

$$X_m^t = \Phi_m^t - \mu * (X_m^{t-1} - \sum_{i=1}^N m_i^{t-1}) \quad (4)$$

Suppliers primarily consider the evolution of demand in previous periods. Through  $\Phi$

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7

$$m = \{D, E\}; \quad \Phi_m^t = \sum_{l=1}^3 (\sum_{i=1}^N m_i^{t-l} * \nu^{t-l}); \quad \sum_{l=1}^3 \nu^{t-l} = 1$$

we introduce a simple weighted average of foregoing quantities demanded. Demanded quantities for each of the two technology designs are again summed up over the whole set of possible technology users for each of the previous three periods and are then multiplied with their respective weights  $\nu$ . Thus no sophisticated expectations about future demand developments are included. Furthermore providers of  $\mathbf{D}$  and  $\mathbf{E}$  react on possibly occurring inventories with a reduction of their supplied quantities in the following period in order to clear inventories. As the sensitivity of the commodities does not allow long-term storage, additional temporal capacity constraints have to be introduced. Hence a parameter for decay is added such that for a share of those inventories a deduction in price will be unavoidable.<sup>8</sup> A graphical illustration of resulting supply curves will be given in section 5. Before that the linkage between demand and supply side as well as further features of the model need to be introduced.

### 4.3 Interaction between Demand and Supply

In order to connect both sides of the market for percutaneous heart valve implementation, the charged prices will now have a major influence on the choice between  $\mathbf{D}$  and  $\mathbf{E}$  for all adopting agents  $a_i$ . For this purpose equation (2) will be modified in the following way:

$$D_i = \begin{cases} 1 & \text{if } \left(\frac{d_i}{p_D^t}\right) > \left(\frac{e_i}{p_E^t}\right) \\ 0 & \text{if } \left(\frac{d_i}{p_D^t}\right) < \left(\frac{e_i}{p_E^t}\right) \end{cases} \quad E_i = \begin{cases} 0 & \text{if } \left(\frac{d_i}{p_D^t}\right) > \left(\frac{e_i}{p_E^t}\right) \\ 1 & \text{if } \left(\frac{d_i}{p_D^t}\right) < \left(\frac{e_i}{p_E^t}\right) \end{cases} \quad (5)$$

$$\text{with } d_i, e_i = \{1, \dots, \rho\} \text{ and } p_D^t, p_E^t > 0$$

Potential technology adopters now also consider the price of the competing technologies when choosing one of them. Adopters with only slight differences in their "natural" preferences,  $d_i$  and  $e_i$ , now might decide contrarily to these preferences as price differentials occur. If the two prices diverge significantly one can expect a considerable shift of demand from one to the other technology and subsequent changes in inventories and produced commodities. Increasing economic pressure on hospital administrations and their employed physicians will increase price sensitivity and thus may impact the choice of technology. It is important to notice, that adopters are not bound to their first choice; instead they reconsider their decision in every single period on the basis of present prices. Since we assume both technologies being equal in terms of functionality

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<sup>8</sup>

$$\mu = \begin{cases} (0, 1] & \text{if } (X_m^{t-1} - \sum_{i=1}^N *m_i^{t-1}) > 0 \\ 0 & \text{else} \end{cases}$$

and quality switching is supposed to cause no difficulties. But if we consider network economies and individual learning curves, situations of technological lock-in may occur. Choices between competing technologies then also depend on the respective overall number of technology users and also on the decisions each actor has made in the past.

#### 4.4 Network Economies

Network economies in our model will simply be defined as a quality progress of a technology. This progress depends positively on the number of respective users and will be modeled in the following way where  $\delta$  represents the rate of network economies:

$$\Omega^m = \delta * X_m^{t-1} \quad (6)$$

$$m = \{D, E\} \quad \text{and} \quad \delta > 0$$

As technological reliability and quality is very important in the areas of cardiac surgery and cardiology, potential improvements will be directly proposed by the users of the technology. The consequential progress resulting from these feedback processes then constitutes an obvious benefit for all technology adopters. Thus the competing firms in our example may exhibit a different technological development and may attain different technology levels. Higher market shares of one technology version may furthermore increase the propensity to switch to this alternative, simply because of reputational reasons. We include the term  $\Omega$  for the effects of network economies in the decision-making process of each actor according to the Arthur-Model (Arthur 1989). Equation (5) will therefore be modified in the following way:

$$D_i = \begin{cases} 1 & \text{if } \left(\frac{d_i + \Omega^D}{p_D^t}\right) > \left(\frac{e_i + \Omega^E}{p_E^t}\right) \\ 0 & \text{if } \left(\frac{d_i + \Omega^D}{p_D^t}\right) < \left(\frac{e_i + \Omega^E}{p_E^t}\right) \end{cases} \quad E_i = \begin{cases} 0 & \text{if } \left(\frac{d_i + \Omega^D}{p_D^t}\right) > \left(\frac{e_i + \Omega^E}{p_E^t}\right) \\ 1 & \text{if } \left(\frac{d_i + \Omega^D}{p_D^t}\right) < \left(\frac{e_i + \Omega^E}{p_E^t}\right) \end{cases} \quad (7)$$

$$\text{with } d_i, e_i \in [1, \dots, \rho] \quad \text{and} \quad p_D^t, p_E^t, \Omega^D, \Omega^E > 0$$

#### 4.5 Individual Learning

Additionally to the overall progress a technology may experience through extensive use, individual capabilities in the handling of a certain technology may improve through constantly employing it. Cardiologists replacing diseased aortic valves with the procedure of a certain supplier get used to it much faster and will be able to handle this technology

version in an easier way. Hence learning-curve effects will also play an important role in the decision-making process on the users' side.<sup>9</sup> Furthermore individual conditions of single hospitals to suppliers may constitute another benefit from consecutively choosing the same technology version. Hence hospitals also benefit from economies of scale. To include learning curve effects we modify the "natural" preferences  $d_i$  and  $e_i$  in the following way, where individual learning impacts on preferences if a certain technology version has been used in two consecutive periods and where  $\kappa > 0$  represents the rate of learning :

$$d_i^t = \begin{cases} d_i^{t-1} * (1 + \kappa) & \text{if } D_i^{t-1} = D_i^{t-2} = 1 \\ d_i^{t-1} & \text{else} \end{cases} \quad (8)$$

$$e_i^t = \begin{cases} e_i^{t-1} * (1 + \kappa) & \text{if } E_i^{t-1} = E_i^{t-2} = 1 \\ e_i^{t-1} & \text{else} \end{cases}$$

## 5 Simulations for Different Scenarios

This section will show the simulation results for a number of settings. Our aim is to show how different changes in the behaviour or in the characteristics of adopters and moreover in the strategies of the competing firms may alter the market outcome. Starting from an initial setting we will develop the model modifications step by step. The simulations will be carried out with a time horizon of 40 periods and for each scenario we apply 100 different sets of random numbers. We will then plot only the average values of the respective variables.

### 5.1 Initial Setting

The basic setting reflects a trivial scenario. The randomly generated preferences take values from one to ten ( $\rho^D = \rho^E = 10$ ). Thus the probability to choose  $D$  or  $E$  is 50 per cent each for all actors  $a_i$  ( $N=300$ ). The share of early adopters among our group of cardiologists is approximately three per cent ( $s=0.03$ ). Inertia parameter  $L$  amounts to 0.75.

Both firms enter the market charging a price of  $p^{t=0}=1000$ . Their marginal costs  $c$  amount to 200. This price-cost relation is only a rough approximation since current reimbursement hospitals receive for a conventional heart valve implementation – thus serving as upper boundary of the pricing scale – are about five times higher than then

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<sup>9</sup> See Arrow (1962) and Jovanovic and Nyarko (1996) for further details on individual learning curve effects.

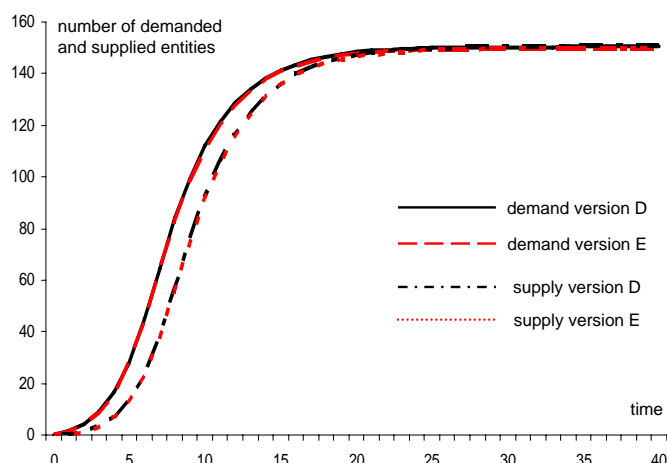


Figure 5: Demand and Supply - Initial Setting.

expected sheer production costs for one unit of the innovative technology. Further parameters of the price formula are defined as follows:  $\varepsilon=0.99$ ,  $\alpha=0.01$ ,  $\beta=0.01$ . Thus both the oligopolistic interdependency between the competitors and the response to possible demand or supply surplus through the price setting are assumed to be weak.

Suppliers weight the demanded quantities of past previous periods weaker the longer those periods are ago ( $\nu^{t-1}=2/3 > \nu^{t-2}=2/9 > \nu^{t-3}=1/9$ ). Due to storage restrictions not all possible inventories can be sold in the subsequent period. Therefore we assume that they reduce supplied quantities not by their full amount in the following periods, but still by seventy per cent ( $\mu=0.7$ ). The network economies parameter is  $\delta=0.01$ . Individual Learning Curve Effects are defined with  $\kappa=0.05$ . Thus preferences for a certain supplier grow with a rate of five per cent through using the technology.

The simulation runs yield curves for demand-, supply- and price-evolution which are (almost) similar for **D** and **E** (figure 5 and figure 4 above). While the supply – due to the specification of the respective formula – lags behind the development of demand during the entire growth period of the market, prices constantly decline before they reach their minimum level at **c**. In this basic case the competing firms, **D** and **E**, are similar in quality and functionality – expressed by equal spans for preferences **d** and **e** – and pursue parallel strategies. The market outcome is therefore similar for both suppliers. While the effects of network economies are not sufficient to cause significant deviations from a 50:50 distribution of market shares<sup>10</sup>, individual learning curve effects

<sup>10</sup> On average the market share of technology version **D** was 50.13 per cent when market saturation



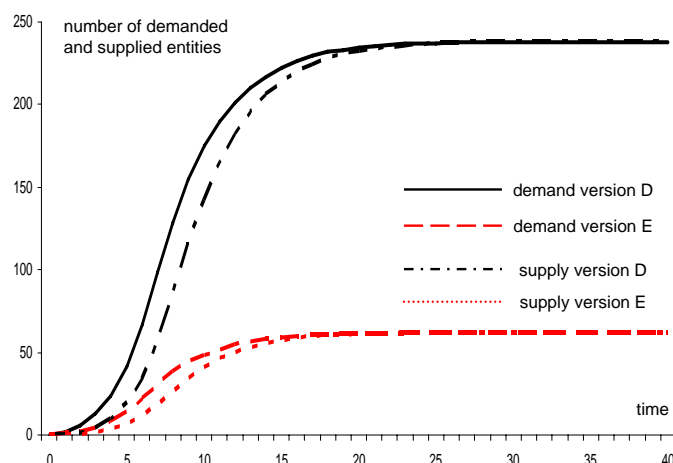


Figure 6: Demand and Supply - Uneven Preferences.

intensify the natural preferences. The even course of demand and supply for **D** and **E** also prevents deviations in prices between the two technology versions.

## 5.2 Uneven "natural" preferences

The first modification we carry out is a rather simple one. We assume that the preferences among our community of cardiologists are higher for technology version **D** than for version **E**. This may result from quality differences, better service offers by supplier **D** or even from stronger preferences for a national supplier in combination with a larger home market for **D**. To incorporate these changes we enlarge the range for the randomly picked adopter preferences for **D** ( $\rho^D=20$ ) while the preferences for **E** remain unchanged ( $\rho^E=10$ ). Note that the probability of being picked is now three times higher for **D** as for **E**. All other settings remain unchanged. The simulation runs for this case are plotted in figure 6.

Competitor **D** captured a market share which is on average only slightly below 80 per cent.<sup>11</sup> Thus network economies amplify the preference differences, so that one out of five actors, who "originally" preferred **E**, decided to adopt the advanced technology version

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was reached. At maximum **D** captured 58.66 per cent of the market, while its lowest market share observed in our 100 simulations was about 42.33 per cent; standard deviation among the market share distributions of **D** amounted to 3.89 percentage points.

<sup>11</sup> The precise average value for the market share of **D** over 100 simulation runs is 79.37 per cent, the minimum value was 71 per cent and the maximum could be found at 85.33 per cent. The distribution of market shares was in this case compared to our initial setting more narrow since the standard deviation decreased to 2.86 percentage points.

**D** instead. Those who stick with **E** over the long run either entered the market in an early stage when the described network economies have not fully unfolded or just show a strong preference for supplier **E**. In either case, by individual experience in handling the specific technology, switching to another version in later stages of the market evolution is no option for these actors. Individual learning curve effects are then clearly opposite to the effects of network economies. Carrying out the simulations in this setting without any individual learning leads on average to a market share distribution of 84 vs. 16 per cent for **D** and **E**, respectively. Interestingly, in none of these 100 modified simulation runs network economies were able to let **D** achieve monopoly-status. Doubling the network effects ( $\delta=0.02$ ) increases the average market share for **D** to almost 95 per cent, but still not suffices to make **E** drop out of the market in any of the 100 simulation runs. What can be observed here is that some agents reverse their decision for **E** in the course of time so that demand and supply curves for **E** show a slight decrease before they reach their final numbers. Only when the network parameter is increased by another percentage point ( $\delta=0.03$ ) almost all adopters finally decide for **D** – only in some cases one or two agents still opt for **E** instead **D**.<sup>12</sup>

Since individual learning seems to be of particular relevance in our cardiovascular example it is worthwhile looking at its relationship to its opposing forces, technological progress rates resulting from user feedback process and reputational effects – both incorporated in the model as network economies – in greater detail. How much effort should supplying firms invest to build up strong personal ties to their consumers in the case they face heterogeneous demand conditions? Or in other words: Under which conditions can reputational and evolving technological gaps not or only hardly be overcome by close personal relations? Starting from our initial situation with uneven preference where  $\rho^D=20$  and  $\rho^E=10$  we keep at first the individual learning rate  $\kappa$  constant at five per cent and run simulations with network effects of varying extent. While the reduction of the network parameter  $\delta$  reduces the differences in final market shares to a level only caused by the uneven distribution of preferences,<sup>13</sup> increasing the extent to which network economies come into play reinforces the initial differences in preferences very fast. Doubling the size of the network parameter ( $\delta=0.02$ ) results in an average increase of

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<sup>12</sup> These observations are of course heavily dependent on the distribution of preferences among our set of potential technology adopters. When shifting the preference even stronger towards **D** (e.g.  $\rho^D=30$  vs.  $\rho^E=10$ ) technology version **E** almost completely drops out of the market with even lower increases of  $\delta$ . But since still some agents opt for **E** instead of **D** until  $\delta$  crosses a certain threshold (comparable to the one above) relatively strong preferences for **E** might still be enough to forgo on possible benefits the alternative technology may reveal due to network effects.

<sup>13</sup> For the different levels of  $\delta$  at 0.5 per cent, 0.25 per cent and 0.1 per cent we obtain average market shares for **D** of 76.87 per cent, 75.76 per cent and 75.12 per cent, respectively.

$D$ 's market share by six percentage points and fixing  $\delta$  at three per cent lets  $D$  obtain on average 93.2 per cent of the market. Further increasing  $\delta$  to four and five per cent leads almost to a monopoly status for  $D$  with average market shares of 98.41 and 99.79 per cent, respectively.

Now we keep the network parameter fixed at five per cent in order to check if there exists a level of individual learning that avoids initial differences in our preference structure to reinforce due to network effects. Simulations with different levels of individual learning rates show that reinforcing mechanism through network effects of this scale can not be prevented by increasing the preference for a certain technology after consecutively using it. Even if we assume that such individual learning rates take on values of 50 or even 100 per cent, a growing divergence of market shares cannot be stopped during the course of market evolution, meaning that the average market share for  $D$  remains always well above 90 per cent. The reasons for this behavior are straightforward. During the period of fast growth,  $D$  attracts more new users simply because of the uneven distribution of "natural" preferences among the potential technology adopters. The higher network effects for  $D$  that result from this preference difference now also attract a significant share of agents originally preferred version  $E$  over version  $D$ . Introducing individual learning effects, even if they are of much bigger size compared to the network effects parameter, are only of importance to agents that nevertheless decide to use technology version  $E$ . This opposing force is therefore only able to restrict the change between the technologies. If sufficiently large the learning parameter makes agents who once chose  $E$  stick with it over the entire course of market evolution. If two firms enter a market facing an uneven preference structure in its early stages it very much depends on the nature of possible network economies if the original divergence in market shares gets reinforced. Network economies of low extent are of minor concern – even more when individual learning plays a role – but if technological progress resulting from user feedback processes can be expected to be of major importance and/or reputation of technology suppliers play a significant role for the choice of technology, markets evolve towards monopolies where the disadvantaged firm can at best prevent that too many of its technology users switch to the competing technology version.

Since the evolution of prices differs only slightly from the one in our basic setting, we leave out the respective diagram. Although  $D$  is facing much bigger demand surpluses and therefore reduces prices to a lesser extent, particularly in the phase of rapid market growth, differences between the two prices are only hardly visible and therefore exert only negligible influence on the distribution of market shares.<sup>14</sup> This is of course due

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<sup>14</sup> The maximum difference between  $D$  and  $E$  remains slightly below 1.5 price units and accounts for

to the marginal impact we attach to possible demand surpluses in our pricing formula. Since we assume the parameter representing price pressure to be the dominant one, the interdependency as well as the parameter relating to the "market sentiment" were initialized at low values. If we abstract from this assumption and increase the demand surplus parameter ( $\beta$ ), not only significant price differences occur, but subsequently this also leads to shifts in the market share distributions, albeit the latter are not of considerable amount.<sup>15</sup>

Deviations in demand between the two competing technologies resulting from unevenly distributed adopter preferences are enforced through the existence of network economies. Though these effects can be partially be dampened through individual learning curve effects and to much lesser extent also through persistent price differentials, they easily lead to situations where a lag in market shares may be hard to overcome.

### 5.3 Delayed Market Entry

The third scenario displays a situation where the competitors enter the new market at different points of time. In our particular example this situation may occur very well since innovative medical technologies have to comply with extensive certification regulations encompassing thorough clinical testing before they can finally be sold to hospitals or other entities. Another reason for a delay in market entries may result from vague patent situations. Patents could still be in the pending-process and therefore not be granted yet. Furthermore there may also be proceedings concerning alleged patent infringements.

But the third scenario may also display situations where the competitors have different production capabilities. Not all firms have equal access to necessary resources. For example, one may think of a competition between a subsidiary of a multi-national company and a small start-up enterprise. Whereas the former can attract financial capital without substantial difficulties, the latter may have problems in funding its production process. As a consequence of uneven factor endowments some firms can supply the entire market, while others operate within narrow restrictions. Referring to our cardiovascular example, new medical technologies and procedures are often developed by (hospital) spin-offs. These firms basically engage in research and development in a certain field to achieve market certification for a specific product. Due to a lack of funds these firms

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only 0.3 per cent of the price actually charged in the respective period.

<sup>15</sup> Simulation runs with  $\beta$  at 0.10, 0.20 and 0.50 led to temporary price differences at most of 3.0, 5.8 and 13.6 per cent, respectively. Expressed in price units this means that prices for  $D$  were at most 15 to 72 units bigger than those of  $E$ . The consequential loss in market shares for  $D$  was nevertheless not bigger than 1.55 percentage points.

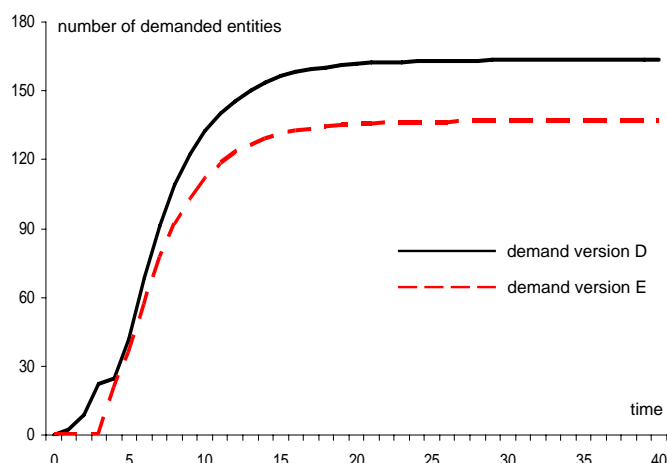


Figure 7: Demand - Delayed Market Entry (3 Periods).

are unable to mass-produce their commodities. Once market approval is obtained, the firms will usually be sold to investors or multi-nationals that are able to serve the entire market. Therefore scenarios with different firm sizes or temporally differing capacity developments may be of interest when modeling the diffusion of competing medical technologies.

In this section we will focus only on possible delays concerning the market entry of competing firms, since the implications in the case of different production capabilities will not differ too much from this setting. For this purpose we modify our model by assuming that supplier **E** will enter the market at different points of time, e.g.  $t = 3, 5$  and 10, while **D** is able to serve demand from the beginning. Agents who "naturally" prefer **E** over **D** are then forced to decide against these preferences as long as **E** is not in the market. All other parameters remain constant. Figures 7, 8 and 9 display the average evolution of demand for three different cases of lagged market entry by firm **E**, each one carried out again 100 times.<sup>16</sup> Though we are able to observe similar outcomes in all three cases - persistently higher market shares for the head-starting company, the evolution over time remarkably differs.

In the first case **D** enters the market three periods ahead of **E** and therefore attracts the entire demand of early adopters independent of their respective "natural" preferences (see figure 7). Although **E** is obviously able to almost completely close the occurring

<sup>16</sup> For the sake of clarity we dropped supply curves here. Supply evolves again very similar to demand, only being shifted to the right in our diagrams.

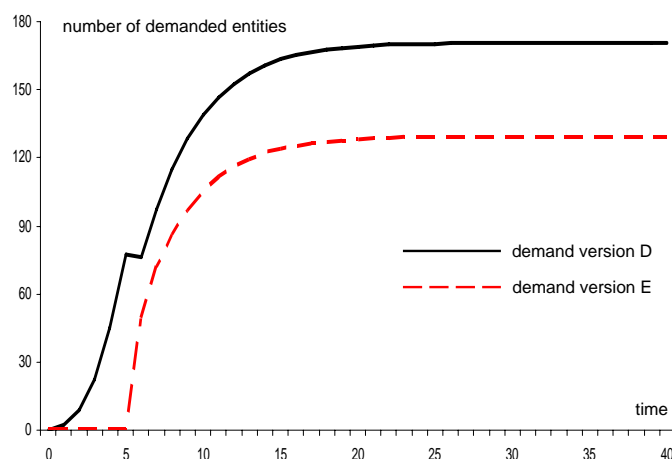


Figure 8: Demand - Delayed Market Entry (5 Periods).

gap as the firm comes out with its own version of the new technology, its competitor is still able to grow with significantly higher rates in the subsequent periods. This behavior results from the combination of individual learning effects and network economies. At the time that **E** enters the market almost all of the agents that "naturally" preferred this technology version switch back from **D** to **E** leading to a sharp decrease in the growth rate of **D** in this period. But more important, some of these adopters nevertheless still stick with their initial choice, mostly out of two reasons: experience they gained through using this technology version and more important also the perceived reputation and reliability **D** was able to build up with the sooner market entry. Starting from this remaining difference in market shares one can observe once again the reinforcing effects of network economies as the divergence becomes more and more important to agents which decide to adopt the innovative technology at later stages of market evolution and thus finally leads to a persistent and significant higher market share for the first mover.<sup>17</sup>

In the second case **E** comes on the market with a delay of five periods (see figure 8). The rationale behind the market evolution we can observe here is similar to the previous case - reinforcement of initial differences in market shares through the combination of individual learning and network economies. In contrast to this case, growth in demand for **D** not only decelerates as its competitor enters the market, but grinds to a halt in that period. As its growth rates take on the same speed as before in the following periods

<sup>17</sup> On average **D** obtained a market share of 54.5 per cent, while standard deviation among these market shares was very low amounting to only 1.06 percentage points, indicating that randomness became less important in the simulation runs.

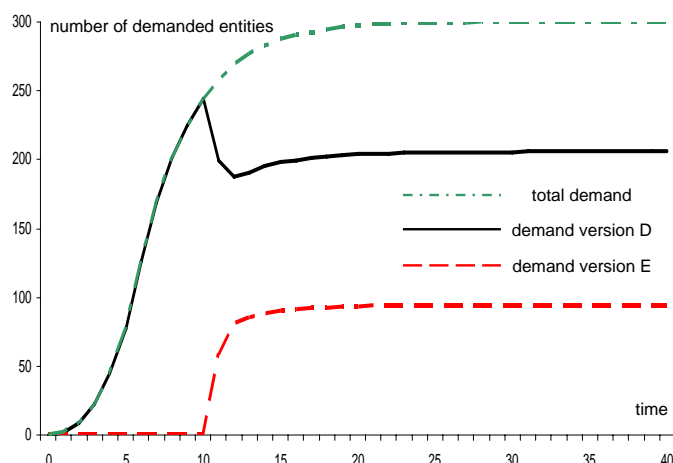


Figure 9: Demand - Delayed Market Entry (10 Periods).

the whole evolution of demand for  $D$  seems only be disrupted for a short moment by the upcoming of a competing technology version. The number of users is rapidly growing for both versions until period 10, before final market shares are obtained with market saturation. The additional lag of two more period led on average to an increase of two-and-half percentage points in market shares for  $D$ .

The final case in this section displays a scenario where one of the competitors enters the market very late. This case is of particular interest as supplier  $E$  comes up with its technology version at a time where the phase of largest market growth is already over (see figure 9). As a consequence the by then already established supplier  $D$  loses a significant share of its demand to  $E$ . A loss in market shares which cannot be coped with the emergence of demand by new agents as the market is already close to saturation. Nevertheless the large head-start of  $D$  saves the firm a market share of almost 70 per cent, which means that almost every second agent "naturally" preferring  $E$  over  $D$  decided against this preference due to the existence of individual learning and network economies.

The conclusions that can be drawn from these three examples are rather simple as late market entry or lagged adjustment of production capacities to the evolution of demand, respectively, may have irreversible long-term consequences, even if these time spans are short. Hence the competition between innovative technologies allows no waste of time for the competing firms in their efforts to reach market certifications as well as in the procurement of funds and other necessary production capabilities.

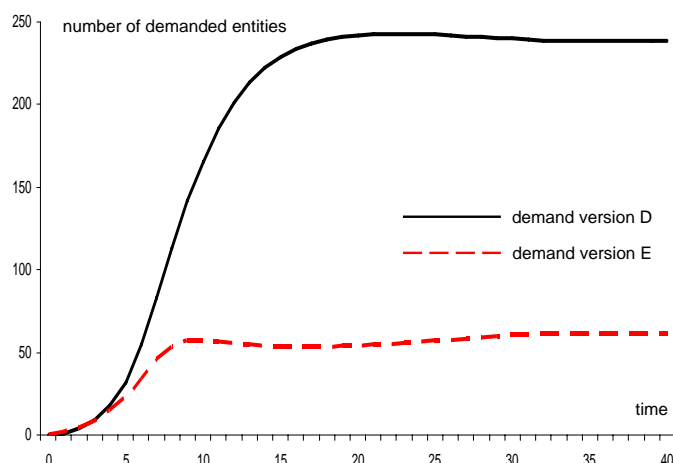


Figure 10: Demand and Supply - Different Price-Cut-Rates.

## 5.4 Varying Price Strategies

After discussing the effects of uneven demand preferences and different time lags we now want to show the properties of two differing market penetration strategies using the price as control variable.

### 5.4.1 Different Price-Cut-Rates

In the first case competitors cut their prices with different extent. For supplier *D* parameter  $\varepsilon$  now takes on a slightly lower value of 0.98. The respective value for *E* (0.99) as well as all other variables remain unchanged. One has to remark that such a parameter change of seemingly minor extent unfolds huge price differentials during market evolution.<sup>18</sup> The plotted simulation run is shown in figures 10 and 11.

The lower prices for commodities *D* unfold their effects already after a few periods. In this case it is price sensitivity which makes some adopters choose a technology they originally do not prefer. Technology version *E* is then only chosen by actors with strong preferences. Once *D* wins a higher market share, network economies again reinforce its predominance. Thus, the distribution of market shares only slightly changes, when the gap between prices diminishes as both reach the same level at marginal costs  $c$ .<sup>19</sup>

<sup>18</sup> The prices for commodity *D* are for more than ten periods at least 200 price units higher than for the competing technology version.

<sup>19</sup> On average *D* holds a market share of almost 80 per cent. As the variance among the market shares for *D* is in this setting almost as high as in our basic scenario, we could find the maximum market share within our 100 simulation runs at 87 per cent and the minimum share slightly below 72 per



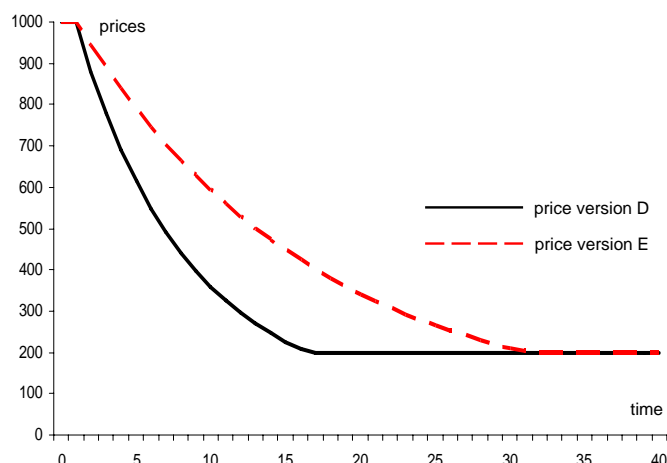


Figure 11: Price evolution - Different Price-Cut-Rates.

As the extent to which we increased the price-cutting rates for technology version *D* were chosen rather arbitrary in our example we also run further simulations with even lower values of  $\varepsilon$  for *D* to check if this would fundamentally change the given picture or even lead to a monopoly for *D*. Interestingly this is not the case. Leaving all other parameters at their initial values and decreasing the value of  $\varepsilon$  for firm *D* increases its market share but only up to a certain threshold (approximately 90 per cent).<sup>20</sup> Thus given the present parameter setting and similar prices at market entry, driving a competitor out of the market is impossible by just cutting the own price very fast. Hence there must exist something like a "optimum" price cut rate which allows to optimize the relation between gains in long-term market shares and the foregone income due to temporary lower prices. Although these considerations rely very much on the setting of the model and its parameters and abstract so far from likely reactions by the competing firm and their subsequent effects on market outcome, the scenario gives first insights on how firm strategies using the price as control variable might work.

#### 5.4.2 Different Prices at Market-Entry

Another starting point for possibly differing market penetration strategies could be the prices firms charge at the time of market entrance. We assume that *E* is charging a fifty

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cent.

<sup>20</sup> The reason for this observation is simply the existence of a minimum pricing level equal to marginal costs which also constitutes a maximum for the divergence in prices between *D* and *E*.

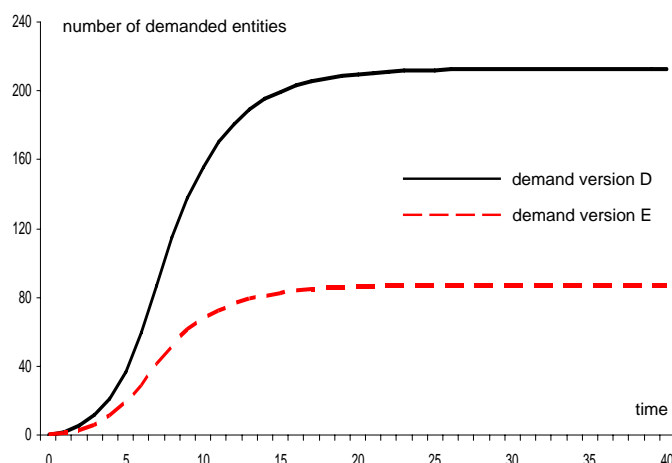


Figure 12: Demand and Supply - Different Prices at Market-Entry.

per cent higher price in  $t = 0$  ( $p_E^{t=0} = 1500$ ). Figures 12 and 13 display the simulation where all other parameters remain again at their initial values.

The now bigger price differences in the early stages again lead to a significant deviation between market shares of **D** and **E**. While price differentials diminish in the course of the market evolution, adopters' preferences for **D** are increased through network economies. As a consequence demand for technology version **E** grows with much lesser speed than the overall market. On the other hand individual learning effects of early **E**-adopters prevent them from reconsidering their decision and switching to the alternative technology in later stages of market evolution. The experience those adopters gained through using the technology outweigh all potential network advantages alternative technologies may display. Interestingly and above all contrary to our previous scenario we cannot observe any loss in market shares for **D** as the gap between prices diminishes.<sup>21</sup> And unlike our first pricing scenario there are no boundaries on possibly occurring price differentials, so that increasing the market entry price for one firm leads to permanent higher market shares for its competitor. Hence it is possible to set up situations where the initial price differentials suffice to create monopoly power for one of the competitors.<sup>22</sup>

Both cases implicate that price differences in an early stage of market evolution unfold

<sup>21</sup> On average of 100 different simulation runs slightly more than 210 out of 300 agents choose technology version **D** in the final period.

<sup>22</sup> However a scenario resulting in a final market share of 100 per cent for one of the firms can – under the current parameter setting – only be achieved when the price charged by the competing supplier is at least more than 60 times higher – therefore a rather hypothetical situation.

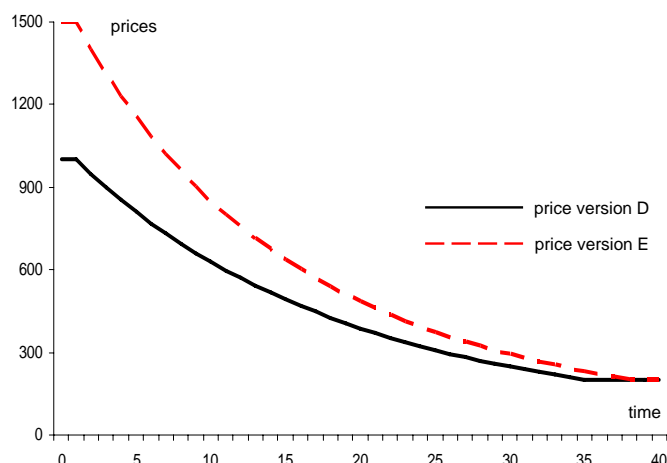


Figure 13: Price evolution - Different Prices at Market-Entry.

long-term effects on the distribution of market-shares. Effects of network economies increase the relative advantage as long as the market is growing, while individual learning-curve effects decrease the vulnerability to market share losses as price differentials diminish in later stages of the market evolution. The scenarios displaying varying pricing strategies also show that an extension of the model with respect to profitability considerations would be helpful to determine the superiority of different firm strategies. What is the price – in terms of foregone profits in early stages of market evolution – that should be paid for long-term gains in market shares?

## 6 Conclusion and Further Research

This paper suggests a simple approach to model the diffusion of two competing technologies. This idea was based on the practical issue of a current research project ("INNOHEART", Friedrich-Schiller-University Jena, Germany) that investigates the innovation process of minimal-invasive cardiologial surgery. The development of a new procedure to implant an aortic heart valve percutaneously and, subsequently, opening up a new business to create a new market in the health care sector is the object of this venture. Facing the high degree of regulation in the medical equipment industry, requiring certification (CE and FDA in Germany and the U.S. respectively) before entering the market, along with the usual specificities of the health care sector such as asymmetric information, deficient consumer sovereignty, etc., an equilibrium model appeared not to

be feasible. Therefore a multi-agent-based model with boundedly rational actors that behave according to rules and learn about a new medical technology in order to eventually make a sound decision best to their knowledge was chosen to put those thoughts into practice. The routine behavior of the suppliers of such minimal-invasive treatment is guided by the reflections on firm size, price setting strategies and demand/supply surpluses. The demand side is modeled using a social learning approach, where the knowledge about the existence of a new medical technology, which involves a more efficient medical treatment, diffuses by interacting physicians (cardiologists) who make the decision to adopt a certain design of a new technology on behalf of their patients. The resulting market structure consequently is influenced by the willingness of potential technology users, to adopt a new technology, the strategic firm behavior subject to network externalities.

Further improvements in future research should focus on possible extensions: institutional aspects of the technology adoption procedure in the health care sector, the competitive overlap with existing technologies, the role of venture capital and its impact on the time-to-market, the role of patent rights, etc.

Still, a lot of work is to be done in order to gain more insights about the technological evolution in the health care sector. Sound policy implications will only be possible, in case we are able to identify the role of the technological progress in the health care sector and thus be able to separate inefficiencies caused by the regulatory system from growth effects induced by technological change.

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