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"Lock-in" vs. "critical masses" – industrial change under network externalities

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Abstract

Where increasing returns to adoption play a role in the diffusion of a new technology, technological "lock-in" is now often claimed to occur. However, this result, and the modeling approach that produces it, are problematic. Further innovations could never have a chance of disseminating, if "lock-in" had occurred in the diffusion process of earlier innovations. Yet, in reality, industrial change does not come to a halt. The paper offers a discussion of the apparent paradox. From an alternative modeling approach conditions are derived under which a newly introduced technology can successfully disseminate in the market despite existing network externalities. © 1997 Elsevier Science B.V.

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JEL classification: C73; L10; O31; O33

1. Introduction

Positive network externalities, i.e. network economies, increasing returns to adoption, or local positive feedback—all terms used synonymously in the literature—are a significant feature of market penetration and diffusion processes of many modern technologies. The feature can be identified, for example, in

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computer operating systems, color television coding standards, typewriter keyboards, and video recording devices. It is easy to imagine the presence of such externalities influencing the innovation decisions on the supply side and the adoption decisions on the demand side. Economic policy makers too may be concerned with the effect of these externalities and feel compelled to push for standardization or to subsidize new technologies which face network diseconomies. Because the consequences of network externalities are so far-reaching they have received increasing attention in the last years from a variety of writers. These authors have used a broad range of concepts and tools for modeling and analysing the implications of the phenomena (Farell, Saloner, 1985; Katz, Shapiro, 1985; David, 1987; Arthur, 1989 to mention a few).

In particular, one branch of the research has focused on the dynamics of the market penetration and diffusion processes and on the inherent tendency towards technological "lock-in" (David, 1985) that, it is submitted, results from increasing returns to adoption (see, e.g., Arthur, 1988; David, 1993). The writers in this camp sometimes argue that the "lock-in" property of such technologies requires government intervention to ensure that the inferior technology does not eventually dominate (Arthur, 1989; David, 1992; for a more sophisticated view see Cowan, 1991). The effects that increasing returns to adoption have, and whether something as dramatic as technological "lock-in" is indeed implied depends, of course, on the assumptions made about the underlying dynamics. The present paper explores these assumptions and raises several questions as to their validity. Some new light can thus be shed on the hypotheses suggested and also on the question of interpretation of technological "lock-in".

The paper proceeds as follows. Section 2 outlines a simple model of strategic decision making by potential adopters and the way a technology with increasing returns to adoption diffuses. The model reproduces the "lock-in" feature discussed in detail by Arthur and others, but, as it emphasizes strategic adoption behavior, the set-up of the model is more along the line of Farell, Saloner (1985) and Katz, Shapiro (1985). Unlike those contributions, however, the present paper explicitly models the dynamics of expectation formation and discusses the mean properties of the resulting stochastic process. On this basis, Section 3 turns to the interpretation of problems which arise when confronting the notion of "lock-in" with the fact that industrial change is obviously of persistent nature. It is argued that certain features of the generalized Polya-urn scheme developed by Hill et al. (1980) and Arthur et al. (1984) induce a misleading deadlock interpretation of the notion of technological lock-in. Section 4 discusses how such an interpretation of increasing returns to adoption can be avoided on the basis of a different modeling approach. The focus is here on the role played by "critical masses" (or critical relative frequencies) of economic agents who, in the face of network externalities, are prepared to switch to newly occurring alternatives. Section 5 offers some thoughts about the policy implications of the changed interpretation and Section 6 some concluding remarks.

2. Strategic decisions in the diffusion of technologies

Network economies frequently arise from technologies which are used multilaterally such as those which enhance, or are instrumental in establishing, direct or indirect inter-personal communication. For illustrative purposes imagine, e.g., a signal processing technology or a signalling language. It usually takes some time before the corresponding devices and capabilities can be established. If there are different variants of such a communication technology for which specific set-ups must be implemented and specific capabilities acquired, it is usually not possible to switch backwards and forwards between these different variants. On the other hand, providing means for using several variants at once, or making each of them compatible, e.g. through signal transformation and modulation, usually imposes substantial additional costs. The agents can save these costs, i.e. realize economies of scale, by using the same variant of the technology in their interactions. The economies of scale are larger the more people stick to the same variant. To put it differently, the individual communication costs arising from the use of a certain variant of the technology depend on the relative frequency with which this particular variant spreads among those who communicate. Therefore, there is a strategic component in the agents' decision making about which technological variant to adopt in such a situation.

To set up a simple framework for analysing the dynamics of adoption and diffusion in the presence of network externalities suppose that, at time t, there are $n(t)$ agents, indexed $i = 1,..., n$, who form a homogeneous population. For lack of more specific information, communication between the members of the population is assumed to occur in a sequence of bilateral acts between randomly determined participants. For simplicity let there be just two alternative variants of the signal processing devices. The strategic aspect can then be expressed in the form of a symmetric game with two strategies v_{i1} and v_{i2} which represent the alternatives available to agent i in the form of adopting variant 1 or 2 of the communication technology. 'Adoption' may mean here, e.g., that agent i leases one of the alternative signal processing devices. The pay-off which accrues from choosing v_{i1} or v_{i2} for future communication is then determined by the intrinsic value and the cost of communication. For convenience, assume that the intrinsic value of communicating is the same for all variants and agents and always greater than the costs so that one variant is always chosen. The costs of the variants may differ for two reasons. First, there may be cost differentials intrinsic to the variants, e.g. for technical reasons. Second, cost differentials arise systematically from the network economies when the two variants disseminate differently.

If the benefit of a single communication act for agent i is denoted by $\pi_i = \pi_i(v_{ik}, v_{jk})$, $i \neq j$, $k = 1, 2$, these particular conditions can be expressed by the order relations

$$\pi_i(v_{i1}, v_{j1}) > \pi_i(v_{i2}, v_{j1}), \quad \pi_i(v_{i2}, v_{j2}) > \pi_i(v_{i2}, v_{j1})$$

and (1)

$$\pi_i(v_{i1}, v_{j1}) > \pi_i(v_{i1}, v_{j2}),\ \ \pi_i(v_{i2}, v_{j2}) > \pi_i(v_{i1}, v_{j2}).$$

In order to specify the modeling framework for the present section in more detail let us explicitly introduce the three assumptions of this section which will be modified or replaced later:

Assumption 1. Potential adopters decide independently on which technology to adopt; their decisions are made in a random order.

Under this assumption the decisions of the agents can, without loss of generality, be treated as being made one after another although some of them may actually be made at the same time.

Assumption 2. The decision of agent i about which variant to adopt is irrevocable and determines the $\pi_i(.)$ for all future communication acts in which agent i is involved.

To make the case for network externalities most explicit, let us ignore, for the moment, all intrinsic cost differentials. This means:

Assumption 3. $\pi_i(v_{i1}, v_{j1}) = \pi_i(v_{i2}, v_{j2})$.

Now consider agent i who is entering the market at time t. The average benefit $E(\pi_i)$ that (s)he can expect from future communications if (s)he has decided to adopt v_k depends on the variants the agents (s)he is going to communicate with have adopted. Because it has been assumed above that communication will emerge from a random matching process, the best guess for the market share of variant k would be the relative frequency $n_k(t)/n(t)$ with which v_k has been adopted by the population at time t (the number of all adopters is denoted by $n_k(t)$). The true value of this random variable is, of course, unlikely to be known to the agents. It may be argued, however, that the agents are able to form subjective estimates ϕ_i of the unknown expected value $F_k(t) = E(n_k(t))/n(t)$. For notational convenience, write $F_1(t) = F(t)$. Given the homogeneous population, the subjective estimates are distributed identically and, since there is no particular reason to assume a source of systematic error, unbiased. This means $E(\phi_i(t)) = F(t)$. The information on which these subjective estimates rely can reasonably be presumed to be less ambiguous the more one of the strategies predominates, i.e. the closer $F(t)$ is to 0 or 1. In the limiting cases $F = 0$ and $F = 1$ the situation may degenerate to one of certainty, while uncertainty, measured in terms of the variance of ϕ_i, culminates in $F(t) = 0.5$. These conditions can be ensured by yet another assumption (which will be retained throughout the paper).

Assumption 4. The subjective estimates of the expected market share of variant 1 at time t are given by a beta-distribution with a probability density function f and parameter $F(t)$, $0<F(t)<1$, as denoted (suppressing the time index) by

$$f(\phi_i|F, 1-F) = (\phi_i^{F-1}(1-\phi_i)^{-F}) \Big/ \int_0^1 v_i^{F-1}(1-v_i)^{-F}\,\mathrm{d}v_i. \tag{2}$$

For ease of exposition let us abstract from any positive discounting of the future and assume that the decision makers are risk neutral. The subjectively estimated benefits which agent i can expect to collect from future communication using one of the variants of the communication technology are then given by

$$E(\pi_i(v_1|F)) = \phi_i(t)\pi_i(v_{i1}, v_{j1}) + (1-\phi_i(t))\pi_i(v_{i1}, v_{j2}) \tag{3}$$

and

$$E(\pi_i(v_2|F)) = \phi_i(t)\pi_i(v_{i2}, v_{j1}) + (1-\phi_i(t))\pi_i(v_{i2}, v_{j2}). \tag{4}$$

Define $D_1 = \pi_i(v_{i1}, v_{j1}) - \pi_i(v_{i2}, v_{j1})$ and $D_2 = \pi_i(v_{i1}, v_{j2}) - \pi_i(v_{i2}, v_{j2})$.

Under the assumptions introduced so far, optimal adoption behavior then prescribes:

Proposition 1. Agent i adopts v_{i1} if the subjective estimate $\phi_i(t) > \phi^* = -D_2(D_1 - D_2)$ and v_2 otherwise.

Proof. Subtracting (4) from (3) a difference $D(t)$ is obtained as

$$D(t) = (D_1 - D_2)\phi_i(t) + D_2. \tag{5}$$

As long as $D(t)>0$ in (5), adopting v_{i1} yields a greater expected benefit than adopting v_{i2} so that the best move agent i can make is to choose v_{i1} (v_{i2} once $D(t)<0$)). Setting $D(t)=0$ and solving (5) for ϕ, the critical value

$$\phi^* = -D_2/(D_1 - D_2) \tag{6}$$

results. The optimal decision rule then is to choose v_{i1} if $\phi_i > \phi^*$ and v_{i2} otherwise.

Note that ϕ^* is identical for all i and $0<\phi^*<1$ because of (1). Moreover, $\phi^*=1/2$ as long as assumption 3 holds. Now let $p(t)$ denote the probability that agent i adopts v_1, at time t, the probability for adopting v_2 being $1-p(t)$. It then follows from proposition 1 (suppressing the time index):

Corollary. Given assumption 4,

$$\begin{aligned} p &= \Pr\{\phi_i > \phi^*|F\} \\ &= 1 - \left[\int_0^{\phi^*} v^{F-1}(1-v)^{-F}\,\mathrm{d}v) \Big/ \int_0^1 v^{F-1}(1-v)^{-F}\,\mathrm{d}v\right]. \end{aligned} \tag{7}$$

Before the implications of these results can be discussed, a way must be found to deal with the so-called incomplete beta-function, i.e. the numerator in the second term of the right-hand side of (7). An exact general solution cannot be determined for this function as is well known in probability theory.[1]

However, for large n the right hand side of (7) can be approximated by the distribution function of a binomial distribution over $F(t)$ with parameters ϕ^* and 1 (see Wilrich, Henning, 1987, p. 48). From the latter, in turn, an approximation of the exact general solution of (7) can be derived which is sufficient to convey the qualitative features on which the argument to be made rests:

$$p(t) = 1 - 1/[1 + 2F(t)\exp(-\alpha(\phi^* - F(t)))], \tag{8}$$

where exp(.) is an exponential function and $\alpha >> 0$ a parameter. For a value $\phi^* = 1/2$ (which satisfies assumption 3) a graphical representation of (8) has been numerically derived in Fig. 1.

Fig. 1 expresses the increasing bias with which the adoption probability of a new entrant bends towards one of the rival variants once that variant has gained a relatively greater acceptance among the existing adopters. What are the implications of the probability function (7), or its approximation by Eq. (8), for the competitive diffusion processes of the two variants in the market? An answer can be given by focusing on the mean process with which the relative frequency of the first variant develops over time.

Proposition 2. If all agents follow proposition 1, a mean process $F(t)$ for the change of the relative frequency of v_1 in the population over time can be derived such that

$$\mathrm{d}F(t)/\mathrm{d}t = g(p(t) - F(t)), \tag{9}$$

where g is a sign preserving function with $g(0)=0$.

A sketch of the fairly involved proof may suffice here:[2] The mean process $F(t)$ is determined by the values which $E(n_1, (t)/n(t))$ takes for each point in time t. According to proposition 1 and its corollary, the agent entering the market during the time interval Δt decides in favor of v_1, on the basis of the test criterion (6) with probability $p(t)$. Suppose $p(t)=F(t)$. In this case, $E(n_1(t+\Delta t)/n(t+\Delta t)) = p(t)(n_1(t)+1)/(n(t)+1)+(1-p(t))n_1(t)/(n(t)+1)$. As can easily be verified, the expected value of the relative frequency thus remains exactly as it is through the additional agent's decision, i.e. $F(t+\Delta t)-F(t)=0$. If, on the other hand, $p(t) > F(t)$, the same calculation shows that $E(n_1(t+\Delta t)/n(t+\Delta t)) > p(t)(n_1(t)+1)/(n(t)+1)+(1-p(t))n_1(t)/(n(t)+1)$ and vice versa for $p(t) < F(t)$. Let $g(p(t)-F(t))$ be a

[1] Tables with numerical values of the function can be found in Pearson (1956).

[2] For a complete proof the reader may consult Arthur et al. (1984).

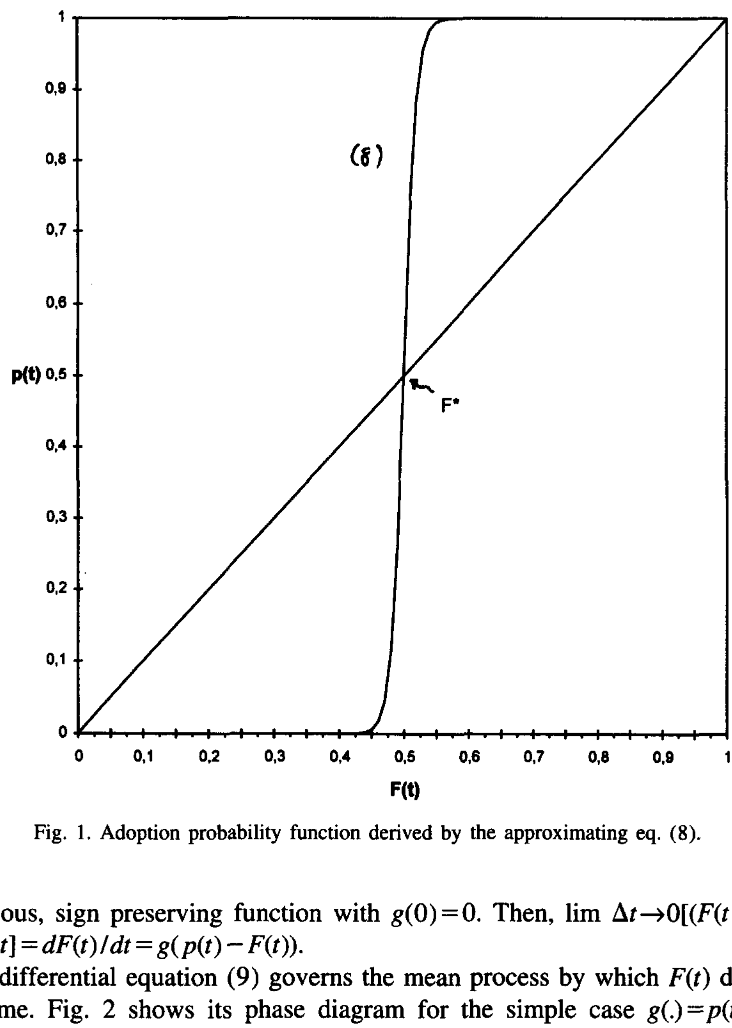

Fig. 1. Adoption probability function derived by the approximating eq. (8).

continuous, sign preserving function with $g(0)=0$. Then, $\lim \Delta t \to 0[(F(t+\Delta t)-F(t))/\Delta t]=dF(t)/dt=g(p(t)-F(t))$.

The differential equation (9) governs the mean process by which $F(t)$ develops over time. Fig. 2 shows its phase diagram for the simple case $g(.)=p(t)-F(t)$ using Eq. (8) in the numerical specification. A necessary condition for a fixed point of the mean process $F(t)$ is $\mathrm{d}F(t)/\mathrm{d}t=0$ which is trivially satisfied for $p(t)=F(t)=0$ and $p(t)=F(t)=1$. These points can easily be identified as locally stable attractors in both Figs. 1 and 2. If a value $\phi^* \in (0, 1)$ exists, we get from inserting (8) into (9), setting $\mathrm{d}F(t)/\mathrm{d}t=0$, and rearranging a solution $F^*(t)$, $0<F^*<1$, which is unique and given by the equation[3]

$$F^*(t) = (1/a)[\ln(1/2) - \ln(1 - F^*(t))] + \phi^*. \tag{10}$$

[3] From Eq. (10) it follows that $F^*(t) \to \phi^*$ as $\alpha \to \infty$. Hence, the intersection of function (8) with the 45°-degree line arbitrarily closely approximates the true intersection point for growing α.

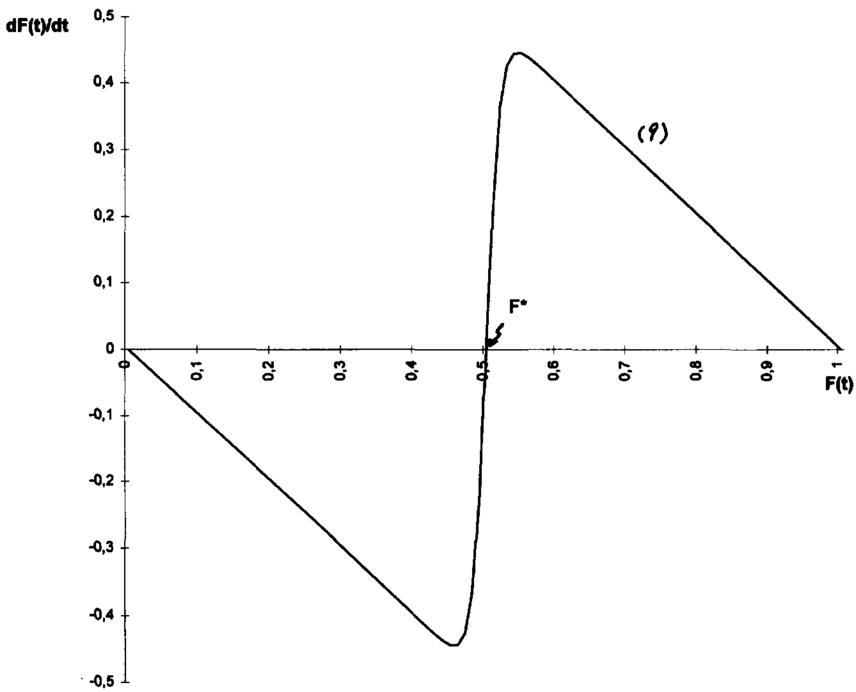

Fig. 2. Phase diagram for change of relative frequency of adopters.

F^* represents an unstable fixed point of the mean process $F(t)$ as can easily be seen from the shape of the graphs in Figs. 1 and 2.

3. "Lock-in" and the problem of explaining change

The interpretation of the results obtained in the previous section crucially depends on the nature of the random processes supposed to govern it and, related to this, on the initial conditions. With respect to the former Arthur et al. (1984), (1987) and Arthur (1988), (1989) have suggested a stochastic process derived from a generalization of the Polya-urn scheme. The focus in their contributions is on a competitive diffusion of rival technological variants. (In contrast to the above, their model is, however, laid out in a non-strategic framework). With respect to the initial condition, this approach implicitly presupposes a situation which may be characterized as the 'virgin market condition'. Imagine a newly invented technology that gives rise to network externalities and which has been developed into two alternative variants. The 'virgin market condition' occurs, if both these variants are introduced at the same time by their producers into a market that did not previously exist.

It takes time for information about the relative frequencies with which the rival variants are used to show up in such a market. In addition to assumption 1 we therefore introduce:

Assumption 5. Up to a time t', $0<t'<\infty$, before which subjective estimates ϕ_i cannot be formed, a number of agents enter the market and randomly choose between the two rival variants in an unbiased way.[4]

For all $t>t'$ the adopters are supposed to have some information available about the relative frequencies with which the rival variants spread. The further development of the number of adopters $n(t)$ is given by

Assumption 6. $n(t)\to\infty$ as $t\to\infty$.[5]

This assumption corresponds to the notion of an infinitely increasing number of randomly chosen balls, red or white, which are imagined to be added to an urn in the generalized Polya-urn scheme. In that scheme, the probability of adding a ball of either color is positively correlated to the relative frequency of balls of the same color already in the urn.[6] In the competitive diffusion case discussed here, such a correlation is supposed to emanate from increasing returns to adoption. Once $t>t'$, the network economies tend to progressively bias the probability (7) of choosing amongst the rival variants towards the variant with relatively more adopters. As proved by Hill et al. (1980) for the generalized urn process, the probability that balls of only one color are added continuously (or, for that matter, that only one of the technological variants continues to be adopted) eventually converges to 1 as the number of balls (adopters) goes to infinity. Likewise, we have:

Proposition 3. Given the assumptions 1–6, the mean process F(t)

1. *remains in the point F^* for $t\leq t'$ and*
2. *converges with equal probability to either $F(t)=0$ or $F(t)=1$ as $t\to\infty$.*

Proof. Part (1) follows directly from assumption 5; part (2) follows from the fact that each random realization of the process is ultimately attracted, after some

[4] This may be taken to mean that the rival variants are either chosen with equal probability or with a probability equal to the relative size of the pay-offs, i.e. $\pi_i(v_{i1}, v_{j1})/(\pi_i(v_{i1}, v_{j1})+\pi_i(v_{i2}, v_{j2}))$ and $\pi_i(v_{i2}, v_{j2})/(\pi_i(v_{i1}, v_{j1})+\pi_i(v_{i2}, v_{j2}))$. As long as assumption 3 holds the two cases need not be distinguished.

[5] Cf. Arthur et al. (1984), (1987).

[6] Corresponding to the set of initial adopters deciding autonomously, the urn is supposed to already contain a limited number of balls of a certain composition of colors when the procedure starts.

random fluctuations around F^*, to either $F(t)=0$ or $F(t)=1$ with probability 1 as $n \to \infty$ as proved in Arthur et al. (1984), (1987).

The competitive diffusion process is thus "locked-in" to one of the rival technological variants. Once one variant predominates each further adopter only reinforces the network externality. This strong result seems to have dramatic implications. In view of the fact that all future adopters will stick to a variant that has won out in the competitive diffusion, further technological change seems endangered, if not prevented. Society might forego significant wealth increases because, even if a new technology or variant were invented which, if generally adopted, would allow all adopters to realize a higher pay-off, this superior solution would appear to have no chance of succeeding.[7] If technological "lock-in" turns out to ultimately mean a deadlock situation, would not technology policy be compelled to intervene?

Before speculating about this question, however, some doubts should be raised about the plausibility of both the theoretical underpinnings of, and the empirical evidence for, technological "lock-in". First, there would be no point in speculating about detrimental effects of technological "lock-in", if there were no possibility of the situation being changed as the probability model of the generalized Polya-urn scheme literally claims. Experience teaches, of course, that, sooner or later, there will always be new rivals who threaten the market dominance of a technology or a variant. The erosion of market dominance under competitive pressure by new technologies supports Schumpeter's (1942, chap. 7) empirical generalization that an "incessant gale of creative destruction" characterizes modern industrial capitalism. It provides no support for the notion of technological "lock-in".

Second, there is a tacit change in the assumed initial condition when it is argued that technological "lock-in" amounts to foregoing wealth increases. The claim that a "lock-in" situation prevents better variants from succeeding is no longer based on the 'virgin market condition'—rather a technological newcomer faces an incumbent technology. A new variant v_2 enters a market in which there is already an established variant v_1. To put it more formally, the initial fluctuations are no longer supposed to start from the unstable fixed point F^*, but from the stable attractor $F(0)=1$. As a matter of fact, there does seem to be a lot in such an interpretation. In reality, markets cannot be taken in isolation as the partial market perspective of the 'virgin market condition' assumes. New technologies, or variants of them, enter a system of markets in which there are already some products, methods, technologies which are potentially substitutes for the new ones. As has just been said, in many cases the existing technologies or variants may have become established by out-competing earlier rivals. It is therefore highly desirable to turn from the 'virgin market condition' to a more realistic interpreta-

[7] See the discussion of the typewriter keyboard case in David (1985) or that of the nuclear power plant technology in Cowan (1990) together with the policy recommendations derived from these cases.

tion of the initial conditions, but this is not possible without making other modifications to the theoretical underpinnings of the stochastic process assumed.

Here a third, related, criticism arises because, in an economic context, some elements of the generalized Polya-urn scheme, which play a key role in proving the emergence of "lock-in", are difficult to justify anyway. It is trivially obvious that the scope of the market for any product is limited. The scope of the market for a new technology is basically determined by its inherent features. The number of potential adopters, the upper bound for the diffusion of the technology, should therefore be seen as a finite constant and not as a continually, indefinitely increasing, number as in assumption 6. Furthermore, unlike in assumption 2, adopters who have already made a choice do not necessarily have to stick to their decisions for ever. In fact, since it is often the same (finite) population that makes up the pool of potential adopters for several successive technologies or variants, the possibility of each of the agents switching between rival variants seems to be a logical prerequisite for treating technological change as an incessant process. Finally, there is the question of whether the notion of potential adopters who enter the market independently, and who choose independently, as in assumption 1, does justice to the fact that all sorts of "diffusion agents" (see Section 5) usually try, for a wide variety of reasons, to influence people's adoption decisions. As can easily be imagined, successful correlation of individual adoption decisions may be a powerful means of counteracting the incentives of network externalities faced by the individuals when they decide independently.

Any attempt to account for these objections obviously requires a modeling set-up which differs in several respects from the generalized Polya-urn scheme discussed so far. The challenge for an alternative model is the following—we need to understand why, in spite of increasing returns to adoption, what has been claimed to be technological "lock-in" is by historical standards a transitory state of affairs. What has to be explained is how technological change can occur in markets where a certain variant of a technology has already become predominant.

4. Technological progress, network externalities, and "critical masses"

Consider a market for a certain well established technology or variant, e.g. a certain technological variant of a signal processing device, to use the example of Section 2 once more. In accordance with the criticism in the previous section, the 'virgin market condition' will now be replaced as an initial condition by the more realistic case in which a new technology or variant enters the market of the existing variant. The new opportunity means that leasing contracts for the old technique may be terminated and contracts for the new technique may be made instead. On the other hand, contracts for leasing the new technique will not necessarily be honored for ever. People may want to revoke them after they have experienced the new technique in practical use and return to the old one. To account for such a setting assumption 2 has to be replaced by

Assumption 2′. When agent i makes the decision, (s)he is already using one variant and makes a choice between switching or not switching to a rival variant.

In addition, assumption 6 has to be replaced by

Assumption 6′. The number of potential adopters of the new technology or variant is $n(t)=n$ for all t.

Let us retain assumption 1 for the moment and assume that, at each point in time, one agent (chosen at random from the population) makes a decision. For simplicity, let there again be only two variants v_1, and v_2 of a technology. As before, the switching decision involves a strategic element. For that reason, the specifications (1)–(8) introduced in Section 2 also apply here. In view of assumption 2′, proposition 1 has to be slightly adjusted, since the number of agents who have adopted one variant can now change as a result of switches in both directions. Under assumption 2′, assumption 6′, and the otherwise unchanged assumptions of Section 2, optimal adoption behavior implies:

Proposition 1′. If agent i uses v_{i2} at time t (s)he switches to v_{i1} if the subjective estimate $\phi_i(t)>\phi^*=-D_2/(D_1-D_2)$ and does not switch otherwise. If agent i uses v_{i1} at time t (s)he switches to v_{i2} if $\phi_i(t)\leq\phi^*$ and does not switch otherwise.

The proof of proposition 1′ can be derived by analogy from the proof of proposition 1. Note that the corollary is still valid so that, according to (7), people using v_2 turn away from it with probability $p(t)$ while people using v_1 turn to v_2 with the tail probability.

Although some significant changes have been made in relation to the set-up of the generalized Polya-urn scheme, it is still possible to prove that the resulting mean process describing the (contingent) diffusion of a new technology or variant has several generic features in common with the model of Section 2. In particular we have:

Proposition 2′. If all agents follow proposition 1′, a mean process $F(t)$ for the change of the relative frequency of v_1 in the population over time can be derived such that $\mathrm{d}F(t)/\mathrm{d}t=p(t)-F(t)$.

Proof. For a small increment of time Δt, the number n_1 of adopters of v_1 changes according to the Chapman–Kolmogorov equation

$$n_1(t+\Delta t)=(1-P(n_2,t+\Delta t|n_1,t))n_1(t)-P(n_1,t+\Delta t|n_2,t)n_2(t). \tag{11}$$

Here $P(n_k,\ t+\Delta t|n_h,\ t)$, $k=1,\ 2,\ h=1,\ 2$, and $k\neq h$, denotes the conditional probability for the transition, during the time increment, of agents using variant h at time t to the alternative variant k. Dividing both sides of (13) by n, we obtain the Chapman–Kolmogorov equation in the relative frequency

$$F(t+\Delta t) = (1 - P(1-F, t+\Delta t|F, t))F(t) - P(F, t+\Delta t|1-F, t)(1-F(t)). \tag{12}$$

Using a Taylor expansion so that $P(F, t+\Delta t|(1-F), t) = p\Delta t + O(\Delta t^2)$ and $P(1-F, t+\Delta t|F, t) = (1-p)\Delta t + O(\Delta t^2)$ and dividing both sides of (12) by Δt we may take the lims and get the master equation[8]

$$\begin{aligned}\lim_{\Delta t\to 0} \frac{F(t+\Delta t) - F(t)}{\Delta t} &= \mathrm{d}F(t)/\mathrm{d}t = (1-F(t))p(t) - F(t)(1-p(t)) \\ &= p(t) - F(t).\end{aligned} \tag{13}$$

Given proposition 2′, the phase diagram of Fig. 2 can be used again to discuss the dynamic features of the (quasi) mean process (Weidlich, Braun, 1993). In order to trace the consequences of the changed initial conditions assume that v_1 is the variant presently used by all agents and let v_2 be the innovative variant entering the market at time $t=0$. Thus, in this interpretation the process does not start in the point F^* but in $F(t=0)=1$, i.e. in a point identified before with the "lock-in" situation, the (upper) right corner in Figs. 1 and 2. The question is whether the modifications introduced to the model have any bearing on the processes emerging from this situation. In particular, it may be asked how the notion of "lock-in" is affected.

The answer to these questions is in several steps. First, let us modify assumption 5 into:

Assumption 5′: Up to a time t', $0<t'<\infty$, before which subjective estimates ϕ_i cannot be formed, those agents making a decision switch to v_2 with probability

$$q = \pi_i(v_{i2}, v_{j2})/(\pi_i(v_{i1}, v_{j1}) + \pi_i(v_{i2}, v_{j2})).^{9} \tag{14}$$

If the number of agents who have made a decision before time t' is $n(t')$, a share $\gamma=n(t')/n$ can be defined. It can be concluded from Fig. 2 that the innovation cannot gain a foothold in the market unless γ is so large that $F(t')$ is driven into the near neighborhood of the critical value F^*. To give a numerical example,

[8] For sake of comparison the master equation is derived here in continuous time. The proof then requires taking the limits which, in turn, presupposes n to have an infinite value. However, this is only a technical requirement. In a discrete version, the master equation approach can easily be shown to possess the same generic features for any large, but finite, n. For a general discussion of the master equation approach see Honerkamp (1994, chap. 6).

[9] (14) reflects the relative size of the maximum pay-off. Note that the basic argument to be made below works, in principle, with any positive probability.

suppose $\gamma=0.1$. By virtue of assumption 3, $q=0.5$ and $F^* \approx 0.5$. Accordingly, $F(t')=0.95$, and the process is thus almost surely driven back to $F=1$ by the network externality.

The network externality effect is obviously still relevant. However, whether it still prevents a new variant from conquering the market is now contingent not only on the parameter values of q and γ, but also on a parameter implicitly determined by assumption 3. This assumption attributes a pay-off to the variant just launched which, when the variant would be generally adopted, does not differ significantly from the pay-off that can presently be obtained from the incumbent variant. The results stated above change if a superior innovation is introduced into the market. Accordingly, let assumption 3 be replaced by

Assumption 3′: $\pi_i(v_{i2}, v_{j2}) > \pi_i(v_{i1}, v_{j1})$.

Suppose, to give a numerical example, $\pi_i(v_{i2}, v_{j2})$ is four times greater than $\pi_i(v_{i1}, v_{j1})$. Then, by assumption 5′, $q=0.2$. Given $\gamma=0.1$, $F(t')=0.92$. Assuming that $\pi_i(v_{i1}, v_{i2}) = \pi_i(v_{i2}, v_{j1}) = 0$, a value of $\phi^*=0.8$ can be derived from Eq. (5). The corresponding shift is reflected in the new position of F^* in Fig. 3.

More generally, we obtain:

Proposition 3′. Under assumptions 1, 2′, 3′, 4, 5′, and 6′, the mean process $F(t)$ which starts in $F(0)=1$

1. *reaches $F(t')$, $0<F(t')\leq 1$, at time t' and*
2. *the more likely converges to $F(t)=0$ for $t\to\infty$, the closer $F(t')$ comes to the critical relative frequency F^* without exceeding it and, a fortiori, the more it exceeds F^*.*

Proof. Part (1) follows directly from assumption 5′; part (2) follows intuitively from the fact that each single realization of the process for $t>t'$ heavily depends on random fluctuations. A single realization is then more likely to be driven by cumulative fluctuations beyond the critical point F^*, the closer to F^* the trajectory is in t' (or is more likely to be prevented from passing back beyond F^* as a result of cumulative fluctuations the further the critical point has already been exceeded); for a complete proof of the convergence properties see Weidlich (1991) and, in an economic application, Weidlich, Braun (1993).

Extending part (2) of proposition 3′ we get:

Corollary. Full dissemination of v_2 and complete substitution of v_1 is more likely, the greater are γ, q and ϕ^*.

Proof. Consider the relation

$$1-\phi^* \gtreqless \gamma q. \tag{15}$$

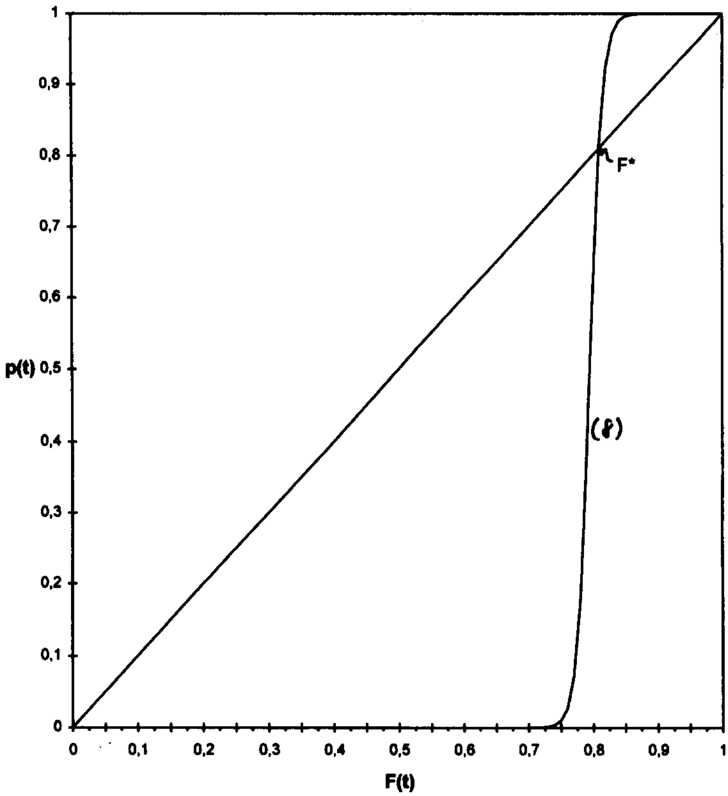

Fig. 3. Adoption probability function for the case of a superior innovation.

The left hand side of (15), taken in isolation, gives a measure for how close F^* gets to 1. The right hand side, taken in isolation, determines the position of $F(t')$. Thus, as ϕ^* grows and the difference on the left hand side of (15) decreases, F^* moves up on the 45° line in Fig. 3. As the product on the right hand side increases when γ and/or q grow, $F(t')$ moves down on the 45° line in Fig. 3. Hence, the critical value F^* and/or $F(t')$ move in the direction of, or even pass, each other so that convergence to $F(t)=0$ for $t\rightarrow\infty$ becomes more likely[10].

Since both the parameters ϕ^* and q grow more the more advantageous v_2 becomes, the suggested model accounts for the fact that technological change is

[10] If the equality holds, (15) can be solved for each of the parameters γ, q, and ϕ^* such that the mean process just takes off from $F(t')=\phi^*\approx F^*$. Since a symmetric game has been assumed, $\pi_i(v_{i1}, v_{j2})=\pi_i(v_{i2}, v_{j1})$. If $\pi_i(v_{i1}, v_{j2})=\pi_i(v_{i2}, v_{j1})=0$, q and ϕ^* take the same value and a critical share $\gamma^*=\pi_i(v_{i1}, v_{j1})/\pi_i(v_{i2}, v_{j2})$ can be derived from (15).

not merely change—it has to be progress in the sense of delivering economic advantages to the individual adopter. For assessing whether, and to what extent, this is the case, it may not only be the inherent cost-benefit characteristics of the new process or product that count, but network economies or diseconomies may also count. This implication resembles an important feature identified by David (1985) and Arthur (1989) in their "lock-in" hypothesis. Notice, however, the contingency of that statement in the alternative modelling set-up presented above: even though the new variant would be advantageous to everyone if more than the critical share F^* of potential adopters made a switch, nobody would make that switch (unless as a result of random influences) as long as $F(t)<F^*$. F^* represents a "critical mass" of adopters that would need to be brought together. In the sciences, critical mass phenomena are a well known feature of nonlinear dynamic systems which imply a bifurcation (see Lorenz, 1993). The master equation (13) above, which implies a pitchfork bifurcation, is a case in point. Critical masses exemplify a point of discontinuity. Once they have been brought together, the attractor towards which the mean process is moving changes abruptly. What previously produced a self-stabilizing tendency towards preserving an established variant induces a dramatic turnaway from self-stabilization once the critical mass is exceeded (see Lesourne, 1989 for a discussion of several examples).

The existence of a critical mass of potential adopters therefore points to another important feature of such nonlinear dynamic systems. In principle, there is always a chance of overcoming what appeared in the previous section to be an inescapable "lock-in" situation produced by increasing returns to adoption—if the new variant is sufficiently superior to the established one. In the presence of stochastic influences there is room for favorable or unfavorable random cumulations. Some technological improvements may be lucky and overcome the critical adoption frequency while possibly 'objectively' even better ones may fail as a result of unfavorable random cumulations. On average, however, it is the extent to which innovations create advantages over those variants in use that counts for their success or failure in disseminating and replacing earlier products or processes.

5. Coordinating adoption: the role of the diffusion agent

The total relative benefit which a newly introduced technology or variant offers is the differential benefit intrinsic to the two techniques adjusted by a detrimental network externality that may have to be incurred at the time the switch from an old to the new technology would have to be made. If the total relative benefit is not positive, it is economically only reasonable for the individual potential adopter to wait for better solutions before switching. The "qwerty" typewriter keyboard (David, 1985) has by now become a prominent example of this case. However, if a new variant has a significant intrinsic differential benefit and only network diseconomies prevent the new variant's general adoption, then it may appear tempting to challenge the wisdom of a general rule that shuns any interference with decentralized market decision making. Because of its strategic element, such a situation has all the ingredients of a coordination game with two equilibrium points, a Pareto-inferior and a Pareto-superior one, where a transition from the inferior to the superior solution would have to be achieved. As discussed elsewhere (Witt, 1992), successful transition in such a game is, in reality, often a matter that needs to be organized—a collective action—because setting the adoption process in motion is like providing a public good. The agents who adopted the new technology or variant at an early stage would have to bear a negative total relative benefit resulting from the initial network diseconomies. In contrast, those who adopt at a time when the diseconomies have already turned into network economies would profit from the 'investments' of the early adopters.

An agent who is trying to organize a coordinated adoption of the new variant by the market participants as a collective action does not necessarily provide a public good her/himself. The profits which the suppliers of a new technology or variant could realize when the critical mass point is overcome in the diffusion of their product may, for instance, make them willing to pay such an agent. Indeed, the role of the "diffusion agent", long known in the diffusion literature (Brown, 1981; Rogers, 1995), can be interpreted in this way. If a major innovation is introduced by larger companies, commercial marketing agencies are regularly engaged for promotion purposes or in-house people are given the job of triggering a diffusion process. In the presence of network externalities, the activities of these diffusion agents do not only consist of spreading the information about the new product or service. Often an attempt is made to coordinate the adoption decisions to avoid the network diseconomies that early adopters would have to bear. Efforts are undertaken during the promotion campaign to convince many potential adopters simultaneously that other customers are also about to adopt the new variant.[11] If the number of potential adopters is relatively small, to come close, or even exceed, the critical mass of adopters it may be sufficient to simply spread information about the names of those who say they are willing to adopt.

With some further modification, the model in the previous section can help in understanding the logic behind those coordination attempts and their success conditions. It makes sense for a diffusion agent to induce potential adopters to make their choices in a coordinated way, provided that it is possible to reach the critical mass point. From that point on network economies could be realized (beyond F^* in Fig. 3) and further adopters could be expected to follow spontaneously thanks to the fact that returns to adoption are now increasing. Convincing many potential adopters at the same time that others are about to adopt as well could thus be turned into a self-fulfilling prophecy. To allow the activities

[11] In addition to these activities the suppliers of the new technology or variant may support the market entry by temporarily charging lower prices—the "special introductory offers" often observed, cf Katz, Shapiro (1986) for an analysis.

of a diffusion agent to have an impact, assumptions 1 and both 5 and 5′ must obviously be relaxed. The effect of organizing collective action is to dispense with the notion of independent individual decision making implicitly invoked in those assumptions. In place of those assumptions let us therefore introduce a new one:

Assumption 1′. Under the influence of the coordinating activities of a diffusion agent, a number n', $0 \leq n' \leq n$, of agents switch during a short time interval $[0, \tau]$ with probability 1 from v_1 to v_2 while no other switches occur. For $t > \tau$ all agents choose independently and in random order which technology to adopt.

If we define $\gamma' = n'/n$ and insert analogously to relation (15) we get

$$1 - \phi^* \gtreqless \gamma'.$$

On this basis a modified corollary to proposition 3′ can analogously be derived:

Corollary. A full dissemination of v_2 and a complete substitution of v_1 is more likely, the greater γ' and ϕ^*.

Proof. The parameter ϕ^* is a measure of the intrinsic differential benefit of the new technology or variant with same impact as before. The parameter γ' measures the efficacy of the diffusion agent. As it goes up, $F(\tau)$ moves down on the 45° line in Fig. 3. Hence, the greater γ' and/or ϕ^*, the more the critical value F^* and/or $F(\tau)$ move in the direction of, or even pass, each other so that a convergence to $F(t) = 0$ for $t \rightarrow \infty$ becomes more likely.

In contrast to markets with relatively small numbers of potential adopters, commercially organized coordination of individual adoption decisions is less likely to be successful in markets with very large numbers of atomistic adopters, like most consumption goods markets. In these cases, private non-commercial organizations sometimes act as diffusion agents and, driven by very different motives, in their attempt to organize collective adoption decisions provide a public good. More often, however, the public good character induces the government to finance agencies to take on the coordinating role of the diffusion agent, or government is encouraged to assume that role itself (Carlsson, Jacobson, 1993). Modern industrial policy oriented towards fostering certain innovations or innovative industries often includes such coordinating activities and may then be beneficial to the public (Gerybadze, 1992).

Where the profitability of new technologies is particularly difficult to assess, or where it is uncertain whether their intrinsic differential benefits are sufficient to induce a critical frequency of potential customers to adopt spontaneously as discussed in the previous section, a coordinating industrial policy like this may indeed encourage private research and development which would otherwise not have been undertaken. There should be no illusion, however, about the fact that a coordinating industrial policy has to draw on uncertain future prospects. Unlike in the models discussed above, which were oriented towards existing technological rivals, the future individual benefits $\pi_{ik}(\cdot)$ of adopting or not adopting a technology yet to be developed are not common knowledge, and presumably not even reliable subjective knowledge. Coordinating industrial policy reaching into the future therefore cannot avoid the risk of 'betting on the wrong horse', of speculating into the wrong direction. Even the performance of Japan's MITI which has often been admired, recently has presented a mixed picture (see Fransman, 1995, chap. 4). The now popular call for the government to take the role of a diffusion agent for technologies of the future may thus turn out to induce failure as often as success.

6. Conclusions

In the diffusion of a new technology, or a variant of it, network economies often play a significant role. If the situation is portrayed as one where a number of rival variants enter a virgin market and compete to gain an advantage in their disseminating, it has been claimed that a situation of technological "lock-in" will eventually result where one variant irreversibly and exclusively dominates the market (David, 1987; Arthur, 1988, 1989). In reality, however, a new technology or variant does not enter a virgin market, nor does industrial change definitely come to a halt because of technological "lock-in". There seem to be some counter factual elements in the modeling approach that produces an interpretation of the "lock-in" phenomenon as an inescapable state of affairs. An alternative model has therefore been suggested in this paper. Instead of the virgin market assumption, a situation where an incumbent technology is challenged by an innovation has been chosen as the initial condition. Since under increasing returns, earlier diffusion processes would have been "locked-in" to the incumbent technology, such an approach quite naturally demands another interpretation of the very notion of "lock-in". A newly introduced innovation could never have a chance of disseminating if irreversible "lock-ins" were indeed to occur.

The alternative model has allowed conditions to be derived under which a newly introduced technology or variant may be able to successfully disseminate in the markets despite existing network externalities. Because these externalities always favor existing and more widely used variants, all success conditions seem to come down to one and the same prerequisite—the capacity to pass a "critical mass" threshold or, more precisely, to attract a critical number of potential adopters who then make an adoption decision. This condition may, in many cases, be considered as a prerequisite for industrial change and, as has been briefly discussed, innovating agents have developed certain strategies to take account of the critical mass phenomenon.

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