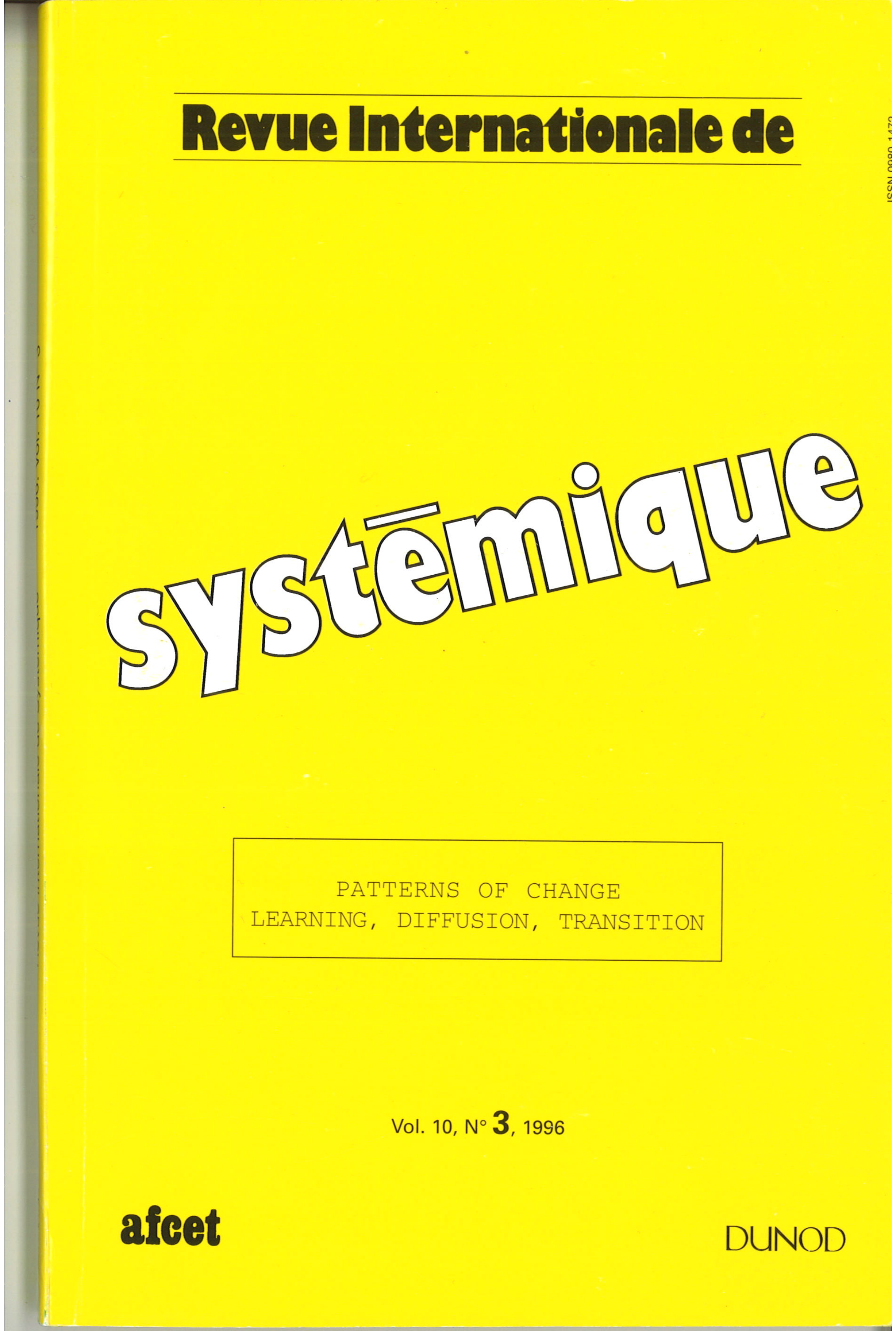

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TECHNOLOGY EVOLUTION AND THE RISE AND FALL OF INDUSTRIAL CLUSTERS*

Peter SWANN [1]

Abstract

This paper explores how the evolution of technologies influences the relative success of different regions or clusters at producing those products. In particular, it explores how the convergence of communications, computing and software technologies influences the relative success of "one-technology clusters" (concentrating on one sub-sector of the industry) and "multi-technology clusters" (with strengths is a number of different subsectors). The paper shows how some multi-sector clusters tend to outperform single-technology clusters when technological convergence is strong..

Résumé

Cet article explore comment l'évolution des technologies influence le succès relatif que connaissent les différentes régions ou zones à produire leurs biens. L'article traite particulièrement de la question de la convergence des techniques de la communication, de l'informatique et des logiciels, et de l'influence qu'elle peut avoir sur, d'une part le succès des zones mono-technologiques (concentration sur un seul sous-secteur d'industrie) et d'autre part, des zones multi-technologiques (concentration sur plusieurs sous-secteurs). L'article montre comment certaines zones multi-sectorielles ont une tendance à mieux réussir que les zones mono-sectorielles, quand la convergence est forte.

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I. INTRODUCTION

Some aspects of technology or product evolution can be described by the addition of further characteristics to the product, and in earlier work this author has argued that the tendency of the dimensions of product space to expand over time is one of the most important aspects of product competition and product evolution. When characteristics are added in this way, the competitive neighbours of any product are likely to change, as was shown some time ago by Archibald and Rosenbluth (1975) [1]. A particularly interesting case arises when formerly distinct technologies and products start to merge together, a leading example of which is the convergence of computers and telecommunications (Arnold and Guy, 1986; Forrester, 1987, pp. 200-204) [2]. As products evolve, the new competitors for a product may come from very different origins.

In consequence, naturally, firms will find that their competitive neighbours will change as products evolve, and that their new competitors may come from industries that they used to think of as quite distinct. This much is well known even if it has not been analyzed empirically as much as it deserves.

This paper goes beyond the implications of product evolution for the network of competitors, to look at the implications for industrial clusters or regions. If the competitive neighbours of a firm change as the product evolves, then so also does the network of companies from which it should ideally like to absorb spillovers. Some of this process of absorption can be done by joint venture at a distance (Hagedoorn and Schakenraad, 1992), but to the extent that geographical proximity is required to enhance this process [3], then the ideal geographical location for the firm may change. More generally, the attractiveness of some clusters may fall because they do not contain the ideal mix of companies and organisational expertise for making the newly evolved product. Conversely, the attractiveness of some clusters will rise as they have a mix of expertise not previously sought after, but now of considerable value [4].

This analysis has some interesting dynamic properties. In some path dependent models of industrial clustering, positive feedback is pervasive –so that when one cluster surges ahead it will dominate the industry [5]. Here, by contrast, some types of product evolution may favour old-established clusters with a high density of more traditional industries over newer, purely high-tech clusters [6].

This paper uses an exploratory econometric model of clustering in the US computer industry (explained in more detail in an unpublished paper, Swann, 1996) to explore this question. A simulation model is developed, based on

that econometric model and is used to explore how different sorts of cluster perform as formerly distinct technologies start to converge.

II. THE METHOD

The main aim of this paper is to see how product evolution, in particular that type of product evolution which follows from the convergence of distinct technologies, influences the relative success of different sorts of cluster. In particular, we want to examine the relative success of specialised clusters (where activity is concentrated in one industry sector) and more general purpose clusters (where activity is dispersed across a number of industry sectors).

To explore this question we proceed as follows. We use our exploratory econometric model (Swann, 1996) of clustering in the US computer industry is a series of simulation experiments. This model (see Section 3) captures the degree of interaction and spillovers between different computer industry sub-sectors by means of two matrices: (1) an *entry attractor* matrix which describes the extent to which a cluster with strength in a particular sector (j) will attract entry to another (i); and (2) a *growth promotion* matrix, which summarises the extent to which strength in one sub-sector (j) at a particular cluster will promote growth of another sector (i) in that cluster.

These matrices can be taken to summarise the interaction between different sub-sectors –rather like the input/output matrix [7]. If the different technologies are not connected (that is there has been no convergence) then it is reasonable to expect that the off diagonal elements of these matrices will be small (possibly even zero). If on the other hand these technologies are strongly interconnected (following convergence between two or more technologies), then it is reasonable to expect that some at least of the off-diagonal elements in the matrix will be strong and positive, because the performance of one sub- sector at a cluster will be dependent on the strength of other relevant (*i.e.* convergent) sub-sectors at that cluster.

The estimated matrices, see Section 3, do have some strong and positive off-diagonal elements, which suggests a degree of convergence. To explore the implications of this convergence process, we perform simulation experiments using a set of possible *entry attractor* and *growth promotion* matrices. In particular, if the estimated matrices are defined (respectively) as Γ and B, then the simulations encompass hypothetical attractor and promotion matrices defined as follows (for different values of σ):

$$\begin{array}{lll} \text{If } i = j : \gamma^*_{ii} = \gamma_{ii}, & \beta^*_{ii} = \beta_{ii} & \\ \text{If } i \neq j : \gamma^*_{ij} = \sigma * \gamma_{ij}, & \beta^*_{ij} = \sigma * \beta_{ij} & [0 \leq \sigma \leq 1] \end{array} \quad (1)$$

The other dimensions of variation in the simulations relates to the initial conditions. Given the vector autoregressive character of the model, the simulation model needs some sort of "kick" to get it started on a growth path. This could be in the form of a pioneering firm (or group of firms) setting up in a new location –and thereby making the foundations of a subsequent cluster. In the simulations we experimented with different sorts of "kick-start". In particular we explored a grid of the 2^8 (= 256) possible permutations: $\{E_i = 0$ or 100 employees in sector i, $i \in [1, 8]\}$.

We conjectured above that specialised (*i.e.* single technology clusters) might do best when the technologies are distinct, but when the technologies start to converge, the specialised cluster will be at a disadvantage compared to the more general purpose cluster. This is essentially the argument of Jacobs (1969) who considers that the most important sources of knowledge spillover are external to the industry in which the firm operates, and that spillovers are strongest in cities with a diverse industrial mix. The results that follow find some support for this thesis in the context of the US computer industry.

III. THE MODEL

The simulation model used here is a straightforward adaptation of our econometric model of clustering in the US computer industry. In this section, we provide a very brief summary of that model; full details of its derivation are given in an unpublished paper (Swann, 1996). The clustering model is in two parts. The first is a model of entry, and the second a model of growth of incumbents for established firms).

III.1. Entry model

The basic entry model is as follows. The number of entrants in any sub-sector (n_{cit}) is a function of employment in each sub-sector at that cluster at the end of the previous period (E_{cjt-1}), and of higher order terms in total employment at the cluster ($E_{c\cdot t-1}$). The precise functional form, however, is a little complex. It can be written:

$$n^*_{cit} = \alpha_{ci} + \sum_{j=1}^{8} \gamma_{ij} \ln E^*_{cjt-1} + \sum_{\theta=2}^{4} \delta_{i\,\theta} (\ln E^*_{c\cdot t-1})^{\theta} + u_{cit} \tag{2}$$

where:

$$n^*_{cit} = n_{cit} - \frac{1}{C}\sum_{c=1}^{C} n_{cit} \tag{3}$$

$$\ln E^*_{cjt-1} = \ln E_{cjt-1} - \frac{1}{C}\sum_{c=1}^{C} \ln E_{cjt-1} \tag{4}$$

$$(\ln E^*_{c\cdot t-1})^{\theta} = (\ln E_{c\cdot t-1})^{\theta} - \frac{1}{C}\sum_{c=1}^{C} (\ln E_{c\cdot t-1})^{\theta} \tag{5}$$

$$E_{c\cdot t-1} = \sum_{i=1}^{8} E_{cit-1} \tag{6}$$

Where C is the number of clusters, and where there are 8 sub-sectors in the model. The parameters α_{ci}, γ_{ij} and $\delta_{i\,\theta}$ are respectively the cluster fixed effects, the attractor effects of particular sorts of employment on entry, and higher order congestion effects. Written in this fashion, it is relatively easy to show that equation (2) satisfies the adding up condition, so that the sum of predicted entry across each cluster equals total actual entry in all clusters.

It is convenient to renormalise the basic model as follows:

$$\begin{aligned} n^*_{cit} = \alpha^*_{ci} &+ \sum_{\substack{j=1 \\ j\neq j_{\min}}}^{8} \gamma^*_{ij} \ln E^*_{cjt-1} + \phi_i \sum_{j=1}^{8} \ln E^*_{cjt-1} \\ &+ \sum_{\theta=2}^{4} \delta_{i\,\theta} (\ln E_{c\cdot t-1})^{\theta *} + u_{cit} \end{aligned} \tag{7}$$

In this normalisation, all the γ^* parameters are positive, which has some advantages –see below. The relationship between these γ^* and the original γ parameters in (2) is straightforward:

$$\gamma^*_{ij} = \gamma_{ij} - \gamma_{ij_{\min}} \tag{8}$$

where $j_{\min}$ is defined as follows:

$$\gamma_{j_{\min}} = \min_{j\in[1,8]} \{\gamma_j\}$$

where the γ parameters are from the un-normalised equation (2). In short, $j_{\min}$ is the sector with the smallest (usually, the most negative) attractor effect in the un-normalised equation (2). The merit of this normalisation is that all the γ^*_{ij} parameters in (7) are positive and can thus be interpreted as attractor effects relative to the least useful sort of employment, while the ϕ_i parameter can be interpreted as a congestion effect: that is, the (probably negative) effect on entry of an increase in the least useful sort of employment. Note also that by definition:

$$\gamma_{ij_{\min}} = \phi_i \tag{10}$$

III.2. Growth model

The growth model examines how growth of employment in each sector depends on cumulative exposure to employment in different sectors at that cluster. Once again, polynomial terms are included to capture the effects of congestion. No adding up restriction can (or need) be applied here, so the model is a good deal simpler as a result:

$$\Delta \ln E_{cit} = \mu_{ci} + \sum_{\substack{j=1 \\ j \neq j_{\min}}}^{8} \beta_{ij} \ln E_{cjt-1} + \psi_i \sum_{j=1}^{8} \ln E_{cjt-1} + \sum_{\theta=2}^{4} \pi_{i\theta} \left(\ln E_{c \cdot t-1}\right)^{\theta} + \nu_{cit} \tag{11}$$

with variables equivalent to those defined above (except that they are not "starred").

The interpretation of the parameters for the growth model are similar to those of the entry model, though slightly different in detail. The parameters in (11) are elasticities, which is convenient for interpretation) while those in (2) and (7) were not. The μ_{ci} terms are cluster fixed effects on growth, and summarise the extent to which a particular cluster (c) tends to experience above (or below) average growth rates in sector i. The β_{ij} parameters describe how an increase in employment in sector j at a cluster will increase (or reduce) the growth of sector i at that cluster. Finally, the $\pi_{i\theta}$ parameters in the growth model summarise the extent to which congestion sets in and constrains further growth.

III.3. Estimates of models

These models were estimated with data on the US computer industry. For further details, the reader is referred to Swann (1994). The models describe entry and growth in eight sectors of the US computer industry over the period 1960-1988. The eight sectors are:

1. Communications
2. Chips (Integrated Circuits)

3. Computer Hardware
4. Computer Distributors
5. Peripherals
6. Computer Services
7. Software
8. Computer Systems

It should be stressed at the start that the data available for this exploratory econometric model had a number of limitations. Moreover, a number of reasonably strong assumptions were required to estimate these models. First, the data on "entry" are in fact data on surviving entry. Transitory entrants who do not survive to the end of the period analysed (1988) are not counted. For the purposes of the present paper, however, it is arguable that this is not too serious because after all it is the contribution to growth made by surviving entrants that concerns as rather than the more transitory contribution of entrants who do not survive.

Second, we do not have employment histories for our sample of firms –only a few isolated points. While it was possible to assemble a reasonably accurate time series of the number of surviving firms in each sector at any date, this is a poor measure of the strength of a cluster because it takes no account of size: IBM is treated the same way as a one man computer services company. For that reason we have computed a rough estimate of employment in each cluster by estimating the size of each relevant firm in each year, assuming that the firm grows steadily at its long run exponential growth rate –which can differ significantly from one firm to another. This is obviously quite a strong assumption, and makes no allowance for cycles in growth, resulting from business cycles, for example. But again, give that these estimates as aggregated across firms, then for the exploratory purposes of the present paper, the data can still give a rough indication of cluster strength.

Third, a substantial number of firms are active in more than one sector of the computer industry, and it is usually difficult to say exactly how to split the workforce between different sectors. Moreover, some giant firms Boeing, for example, are important participants in parts of the computer industry, but clearly only a proportion of their employment should be counted for our present purposes. To handle these questions, a number of simplifying –and quite strong– assumptions had to be made. Nevertheless, a number of cross-checks using much simpler models confirms the essential character of the models used for simulation in this paper.

Tables 1 and 2 give the estimates for these two models. The fixed effects for each state are not shown here. Table 1 shows the entry attractors (γ) and Table 2 the growth promoters (β). In the entry model there are some quite strong cross-sectoral entry attractions –particularly from hardware, systems and chips (components) to software and peripherals. In the growth model, on the other hand, the cross-sectoral growth promotion effects are weaker, and if anything the direction of the effects tends to be reversed –so that software and peripherals tend to promote growth in hardware, systems and communications.

Table 1. Entry Model. Gross Attractor and Congestion Effects.

	Equation for sector							
	1	2	3	4	5	6	7	8
1	0	.002	.011	.029	.012	.024	.024	.023
	(–)	(.009)	(.013)	(.009)	(.027)	(.013)	(.034)	(.009)
2	.018	0	.076	.054	.167	.022	.206	.036
	(.011)	(–)	(.018)	(.012)	(.036)	(.017)	(.048)	(.012)
3	.018	.008	0	.030	.069	.009	.130	.033
	(.008)	(.009)	(–)	(.009)	(.027)	(.012)	(.033)	(.010)
4	.009	.001	.002	0	.003	.021	0	.024
	(.009)	(.010)	(.014)	(–)	(.026)	(.012)	(–)	(.011)
5	.016	.005	.005	.019	0	.021	.024	.021
	(.009)	(.010)	(.014)	(.008)	(–)	(.010)	(.033)	(.012)
6	.014	.000	.021	.025	.032	0	.055	.024
	(.009)	(.010)	(.013)	(.008)	(.021)	(–)	(.031)	(.012)
7	.014	.006	.018	.021	.045	.031	.013	.030
	(.008)	(.008)	(.014)	(.008)	(.029)	(.013)	(.031)	(.010)
8	.014	.003	.028	.045	.100	.018	.137	0
	(.008)	(.009)	(.014)	(.010)	(.034)	(.016)	(.039)	(–)
SUM	–.013	–.005	–.011	–.024	–.035	–.020	–.055	–.023
	(.006)	(.008)	(.009)	(.006)	(.019)	(.008)	(.023)	(.008)
SUM^2	–.057	–.025	–.134	–.077	–.385	–.085	–.349	–.039
(* 10)	(.036)	(.031)	(.057)	(.036)	(.110)	(.052)	(.140)	(.041)
SUM^3	.011	.004	.023	.014	.064	.016	.054	.006
(* 10)	(.006)	(.005)	(.010)	(.006)	(.019)	(.009)	(.024)	(.007)
SUM^4	–.006	–.002	–.012	–.007	–.030	–.009	–.023	–.003
(* 100)	(.003)	(.002)	(.004)	(.003)	(.009)	(.004)	(.011)	(.003)
R^2	.15	.27	.36	.14	.47	.14	.36	.18
ESE	.17	.14	.27	.17	.52	.24	.65	.19

Note: Figures in parenthese are standard errors

The other result of importance is the higher order total employment effects in each equation. There are a little difficult to interpret as they stand, but it can be shown that they imply a cycle of entry. At low levels of total

Table 2. Growth Model. Gross Promotion and Congestion Effects.

	Equation for sector							
	1	2	3	4	5	6	7	8
1	.034	.014	.007	.004	0	.025	.004	.019
	(.009)	(.005)	(.013)	(.019)	(–)	(.011)	(.017)	(.009)
2	.009	.033	.022	0	.029	.026	.018	.021
	(.012)	(.008)	(.019)	(–)	(.019)	(.016)	(.022)	(.012)
3	.029	0	0	.012	.005	0	.065	.033
	(.010)	(–)	(–)	(.019)	(.014)	(–)	(.019)	(.010)
4	.011	.008	.027	.036	.011	.016	.014	.033
	(.011)	(.006)	(.014)	(.021)	(.015)	(.012)	(.018)	(.011)
5	.038	.020	.045	.036	.013	.008	.034	.027
	(.012)	(.006)	(.015)	(.020)	(015)	(.012)	(.022)	(.012)
6	.025	.001	.047	.024	.015	.011	.020	.030
	(.013)	(.005)	(.014)	(.020)	(.015)	(.012)	(.020)	(.012)
7	.021	.006	.027	.011	.017	.035	0	.032
	(.010)	(.006)	(.014)	(.017)	(.013)	(.012)	(–)	(.010)
8	0	.001	.004	.056	.043	.011	.011	0
	(–)	(.006)	(.015)	(.018)	(.014)	(.012)	(.019)	(–)
SUM	–.020	–.007	–.023	–.019	–.012	–.017	–.030	–.028
	(.008)	(.004)	(.009)	(.016)	(.010)	(.008)	(.012)	(.008)
SUM^2	.080	.016	.104	–.034	.033	.125	.129	.027
(* 10)	(.037)	(.021)	(.053)	(.054)	(.055)	(.045)	(.072)	(.037)
SUM^3	–.012	–.002	–.015	.014	–.000	–.020	–.012	–.003
(* 10)	(.007)	(.004)	(.010)	(.010)	(.010)	(.008)	(.013)	(.007)
SUM^4	.005	.000	.006	–.007	–.002	.009	.006	.001
(* 100)	(.003)	(.002)	(.005)	(.005)	(.005)	(.004)	(.006)	(.003)
R^2	.28	.41	.17	.20	.15	.24	.09	.29
ESE	.19	.11	.26	.27	.27	.23	.36	.18

Note: Figures in parentheses are standard errors

employment in a cluster, entry is small. Entry then starts to rise as total cluster employment rises, but beyond a certain point, congestion clearly sets in and entry drops off again [8]. This effect plays an especially important role in the simulations of the next section. All these results are discussed in much more detail in Swann (1996).

IV. SIMULATIONS

The simulation model uses the above estimates for the normalised entry model (7) and the growth model as a starting point [9]. As noted above, we want to explore the implications of the convergence process between different technologies (or industry sub-sectors), and to this end we perform simulation experiments using a set of possible *entry attractor* and *growth promotion* matrices. In particular, the simulations encompass hypothetical attractor and promotion matrices defined as follows (for different values of σ):

$$\begin{array}{ll} \text{If } i = j: \gamma^*_{ii} = \gamma_{ii}, & \beta^*_{ii} = \beta_{ii} \\ \text{If } i \neq j: \gamma^*_{ij} = \sigma * \gamma_{ij}, & \beta^*_{ij} = \sigma * \beta_{ij} \quad [0 \leq \sigma \leq 1] \end{array} \qquad (12)$$

The other dimensions of variation in the simulations relates to the initial conditions. Given the vector autoregressive character of the model, the simulation model needs some sort of "kick" to get it started on a growth path. This could be in the form of a pioneering firm (or group of firms) setting up in a new location –and thereby making the foundations of a subsequent cluster. In the simulations we experimented with different sorts of "kick-start". In particular we explored a grid of the 2^8 (= 256) possible permutations: $\{E_i = 0$ or 100 employees in sector i, $i \in [1, 8]\}$.

Starting with a vector of initial conditions for employment in a cluster, the simulation model computes entry and growth in each period, and then accumulates that entry and growth into the employment estimates for the next period. The simulations are run forward for 50 periods, and final employment in each sector is recorded.

In short we have simulations for the 256 types of kick start and 4 values of the convergence parameter σ. These are far too bulky to reproduce in full, but Figures 1 and 2 describe a two typical sets of results for two particular

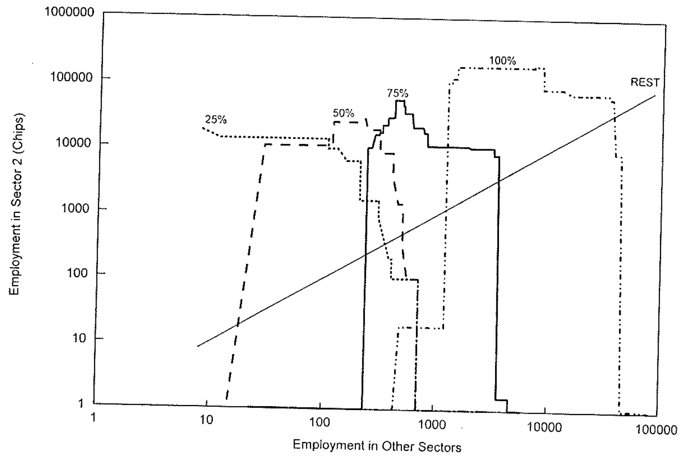

Figure 1.

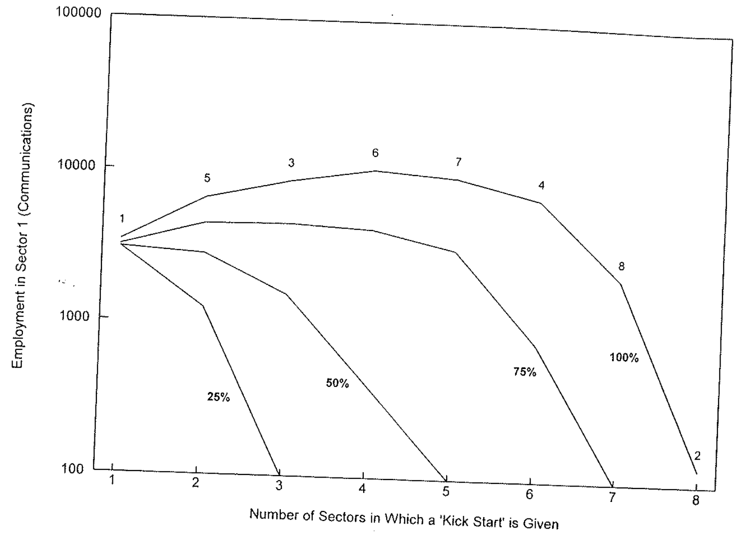

Figure 2.

sectors, and Table 3 summarises the main points of importance in the set of simulations for all sectors [10].

Figure 1 shows the maximum [11] level of employment in sector 2 (Chips) obtained in the simulations for a given total employment in all other sectors. Figure 2 shows the maximum level of employment in sector 1 (Communications) across all relevant simulations, when the simulation is given a "kick start" in n sectors –for $n = 1, \ldots, 8$. In each case the four different lines refer to different values of the convergence parameter (σ = 25%, 50%, 75%, 100%). Table 3 shows for each sector, how the level of employment reached in the sector depends on the convergence parameter (σ = 50%, 75%, 100%) and whether the number of "kick-starts" is administered is right ($N = N_{\max}$), too few ($N = 1$), or too many ($N = 8$).

5. INTERPRETATION OF SIMULATION RESULTS

The basic story is the same for most sectors. In Figure 1, peak employment in the sector occurs further and further to the right as the convergence parameter is increased from 25% to 100%. Moreover, the peak itself increases as the convergence parameter is increased. Finally, the curves for different convergence parameters intersect. With low employment in other sectors, the

Table 3. Relative Employment with "kick-start" in Sector.

	Relative employment with:					"Kick Start" in sector:							
	Convergence	N_{max}	$N = N_{max}$	$N = 1$	$N = 8$	1	2	3	4	5	6	7	8
1	100%	4	100.0	32.1	1.2	1		1		1	1		
	75%	3	43.0	29.8	0.9	1		1		1			
	50%	1	28.6	28.6	0.9	1							
2	100%	5	100.0	39.1	27.3	1	1		1	1			1
	75%	3	27.6	8.0	0.4	1	1			1			
	50%	3	14.1	5.3	0.0	1	1			1			
3	100%	4	100.0	21.7	32.1			1	1	1	1		
	75%	4	26.4	11.4	14.7			1	1	1	1		
	50%	2	11.8	11.5	11.5		1	1					
4	100%	4	100.0	6.5	0.2				1	1	1		1
	75%	3	6.7	0.1	0.1				1	1			1
	50%	2	0.3	0.1	0.1				1				1
5	100%	5	100.0	4.6	30.6		1			1	1	1	1
	75%	4	7.3	0.2	0.2		1			1		1	1
	50%	2	0.8	0.2	0.2					1			1
6	100%	2	100.0	77.4	33.8						1	1	
	75%	2	68.6	52.3	33.9						1	1	
	50%	1	52.0	52.0	33.9						1		
7	100%	3	100.0	11.6	8.9			1		1		1	
	75%	2	75.6	5.1	1.9			1				1	
	50%	2	13.6	2.2	1.9			1				1	
				Frequency		3	3	5	3	10	5	4	7

peak employment in sector 2 is reached with a low convergence parameter (25%) while with a high level of employment in other sectors, the peak employment in sector 2 is reached when convergence is high (100%).

How are these observations to be interpreted? Firstly, if convergence is low, peak employment in a sector is reached when employment in other sectors is low, but if convergence is high, then peak employment is reached when employment in other sectors is higher. This is really just the observation that when convergence between technologies is low, the best performing clusters are the single-technology clusters. Clusters which have moderate employment in several sub-sectors will tend to get congested, and this detracts from employment growth in any one sub-sector. Conversely, when convergence is

high, the best way to grow employment in a particular sub-sector is to exploit the many spillovers between sectors [12], and this requires high employment in other sectors. Even here, congestion eventually sets in. In Figure 1, when convergence is high (100%), it is clear that employment in other sectors must exceed 1,000 to reach peak employment in sector 2 (chips), but when employment in other sectors goes far above 10,000 then the employment level reached in sector 2 starts to dip –again a result of congestion.

Secondly, the fact that peak employment increases as the convergence parameter increases follows simply from the observation that as the technologies converge, so too does the degree of positive feedback in the simulation model. The increase in the peak is not spectacular, but important nevertheless.

Thirdly, the fact that with low convergence peak employment is found where other-sector employment is low, while with high convergence the peak is found where other sector employment is low, while with high convergence the peak is found where other sector employment is high, suggests the following. With low convergence, single-technology clusters have an advantage over multi-technology clusters, because the latter do not generate much in the way of useful spillovers, but do generate congestion effects. Conversely, with high convergence, it is necessary to be in a multi-technology cluster to take best advantage of the rich spillovers –though not an omni-technology cluster, because there congestion sets in too fast.

Figure 2 gives perhaps an even simpler illustration of the simulations. It shows the relationship between peak employment in Sector 1 (Communications) and the number of sectors in which a kick start is administered. Three main observations can be made. First, for any particular level of convergence, the peak level of employment is reached when a "kick start" is administered in an intermediate number of sub-sectors. Second, the optimum number of sectors in which to apply a kick start increases as the level of convergence increases. And third, the peak employment level reached increases as the rate of convergence increases.

The third observation was already made in the context of Figure 1. The first and second observations are also broadly compatible. When convergence is 100%, peak employment is reached with a kick-start in 4 sectors: as before, the diversified, multi-technology cluster does best when technologies converge. But when convergence is low (25%), the best initial conditions are to apply a kick-start in one sector only –the "home" sector indeed. With little convergence there is little cross-sector positive feedback, and congestion effects set in sooner in multi-technology clusters.

Table 3 summarises these results across all sectors. For sectors 1-5, the right number of sectors in which to apply a "kick-start" is 4 or 5 –while in sector 7 (software) and sector 6 (services) the number is smaller.

For each sector, the employment levels achieved with 100% convergence and when the optimum number of kick-starts is given are normalised at 100. The table then shows how the employment level reached declines as the convergence parameter is reduced (to 75% and 50%), and if "kick-starts" are administered in only one sector ($N = 1$) or in all sectors ($N = 8$). What this shows is that the employment levels reached in sectors 4 and 5 are very sensitive to the value of the convergence parameter, and in sectors 1, 2, 3 and 7, there is a fair degree of sensitivity. It is also clear that in sectors 1, 4 and 7, a kick-start in all sectors is seriously counter-productive, with ultimate employment much reduced because congestion effects start to limit the growth of the sector quite early on. Sectors 4, 5 and 7, on the other hand, will not flourish in isolation: the employment levels reached when only one "kick-start" is given in their own sector, is much less than the maximum attainable.

The right-hand side of the table also shows the optimum set of "kick-starts" for each sector and convergence rate. If a 1 is shown, then a kick start is required in that sector; if not, then it is not. In all cases, the optimum kick-start for sector i (say) requires a kick-start in that sector i. These are shown in bold. The last row of the table (Frequency) shows the number of times that a kick-start is required in sector i to achieve an optimum outcome in another sector j. (The fact that a kick-start is required in i to achieve the optimum result in i, is not counted.) Sector 5 (peripherals) emerges as the sector most in demand: for the six other sectors shown (1-4 and 6-7), and the three convergence parameter values considered, a kick-start is desirable in this sector in 10 out of 18 cases. The system sector (8) is also in demand. This means that the most successful performance in other sectors will be observed in clusters where the peripherals sector is at least reasonably strong. On the other hand, communications (sector 1), chips (sector 2) and distributors (sector 4) are less in demand. Clusters weak in these three sectors are less likely to see other sectors suffer as a result.

6. CONCLUSIONS

The main implication of these simulations, therefore, is that the performance of a particular sub-sector of the computing industry at a particular cluster

depends on both the diversity of the cluster (does it specialise in one technology, or is it multi-technology) and the degree of convergence between the different computer technologies. When technologies have not converged, so that positive spillovers between different sub-sectors are limited, then the single- technology cluster outperforms the multi-technology cluster, essentially because in the latter (multi-technology) case, congestion starts to restrain growth in one sub-sector earlier that in the former (single-technology). When the technologies converge, on the other hand, the multi-technology cluster outperforms the single-technology cluster because the former exploits the inter-sectoral spillovers that the latter cannot have. There is however an optimum number of sectors: if a cluster starts with strengths in all sub- sectors of the industry, then congestion sets in too soon to allow full development of any one of these sub-sectors.

To return to the title of the paper, we see a cycle whereby single-technology clusters grow most rapidly when there is little or no convergence, but when technologies start to converge and congestion emerges in early-established clusters, the most successful clusters at a later stage may be multi-technology, and the single-technology cluster declines in relative importance.

In a related paper, Swann and Prevezer (forthcoming) compare the clustering dynamics of computing and biotechnology in the USA [13]. We have not yet attempted to develop the simulation model presented here for the biotechnology case. Our conjecture is that because the cross-sectoral entry attractor effects are weaker at this time in biotechnology than in computing, the single-technology cluster may be quite competitive in that industry. The strength of the science base seems to be the most important factor in attracting entry in the case of biotechnology, but this may reflect the fact that relatively speaking biotechnology is in its infancy [14]. Moreover, our research suggests that the congestion effects are not likely to be as important in biotechnology yet. But if the different parts of that industry start to converge in the same way as modelled here, then the multi-technology cluster may become the most competitive in biotechnology too.

Notes and references

1. See Swann (1993) for an illustration.
2. A related area of analysis is the changing constituents technologies that make up a technological system (Gilles, 1978).
3. The conditions under which proximity is required for technology transfer are discussed in Pavitt (1987), *inter alia*. There is a growing literature which discusses such technological spillovers, and explores whether the strength of these spillovers

decline with distance (Jaffe, 1986, 1989; Jaffe *et al.*, 1993; Acs *et al.*, 1992; Feldman, 1994; Audretsch and Feldman, forthcoming).

4. Davelaar and Nijkamp (1990) present a simulation of model of how technological innovation leads to spatial transformation. Herbig and Golden (1993) give examples of how innovations lead to spatial redistribution of economic activity, and note that some old clusters can reemerge from their decline.

5. For an excellent review of some of this path-dependent literature, see David and Greenstein (1990).

6. Herbig and Golden (1993) place the post-war resurgence of Boston in that category. See also Dorfman (1988). The story of Silicon Valley is, of course, rather different (Saxenian, 1985, 1994; Oakey, 1985).

7. The difference is that the input-output table measures demand side linkages, while the *entry attractor* and *growth promotion* effects described here are a mix of demand side multipliers and supply side spillovers. Scherer (1982*a*, 1982*b*, 1984) has shown how patent and R&D data can be used to estimate interindustry technology flows. Grilliches (1992) provides an excellent review of scientific and technological spillovers.

8. The congestion described here arises in part because of increased competition on the demand side, but also because in fast growing clusters there may be bottlenecks in the supply of important factor inputs. Rosenberg (1976, 1982) has analysed the origin of technological bottlenecks and possible solutions to them.

9. The only differences is that the fourth order employment effects in some of the growth equations had to be constrained to zero, since as they stand they would imply explosive growth in the largest clusters –an implausible, if not physically impossible implication.

10. No simulations are summarised for Sector 8 (Systems) because the model fails to predict any endogenous growth or entry in this sector.

11. As such these lines represent the upper hull of the data. Though not drawn here, if the other simulation results were plotted on the graph, the points would lie below the lines shown. Strictly speaking this is an *undominated hull* and not a *convex hull* since convex combinations are not taken in computing the lines.

12. The study by Mensch (1979) recognises that a trigger is required to fire a new wave or cluster of innovations, and the convergence of technologies offers just such a trigger.

13. Prevezer (1994) gives more detail about the biotechnology clustering model.

14. Bania *et al.* (1993) argue that the science base will be most important in attracting entry during the formative stages of an industry, and show that it will not always have a strong effect on entry.

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THE ACCELERATION AND SLOWDOWN OF TECHNICAL PROGRESS IN THE US SINCE THE CIVIL WAR: THE TRANSITION BETWEEN TWO PARADIGMS*

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Abstract

This paper analyzes the basic features of technical and distributional changes in the US since the Civil War as the expression of the gradual emergence of a new paradigm, corresponding to a Managerial Revolution, and its replacement of the earlier organization inherited from the Industrial Revolution. A stochastic model of technical change of evolutionary inspiration is presented that accounts for the profiles of technology and distribution, within each paradigm. (Innovation is random, and new techniques are selected depending on their profitability). By averaging the two sectors of the productive system corresponding to each paradigm, it is possible to reproduce the historical trends for each variable. For example, the model explains why the productivity of capital and the profit rate displayed successively downward, upward, and downward trends over the three subperiods, 1869-1910, 1910-1950, and 1950-1992. Both the emergence and erosion of the favorable features of the intermediate period, 1910-1950, are explained by the diffusion of the new paradigm.

Résumé

Cette étude analyse les caractères fondamentaux des changements de la technique et de la répartition aux États-Unis depuis la Guerre de Sécession, comme l'expression de l'émergence progressive d'un nouveau paradigme, correspondant à une Révolution Managériale, et

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