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Structure and Dynamics of high-tech clusters: an econometric exercise

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Structure and Dynamics of high-tech clusters: an econometric exercise*

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ABSTRACT

Aim of the paper is to empirically test the relevance of the following statement: "high tech cluster are the future of industrial district". Through an original database (based on census data from USA, UK, France and Italy) on the number of high tech firms and their employment at two geographical levels FLA and SLA (First and Second Level of Analysis) the different models are tested. The first model identifies the most relevant locational factors for high tech firms (based on a cross section estimation of US States data). The second model (based on the complete international data set) tests the relative strength of agglomeration versus scale economies in determining the geographical specialisation in high-tech industries and analyses a series of phenomena connected to the interaction between FLAs and SLAs (i.e. locational shadowing). The third model (built on a cross section estimation of US States data and based on Glaeser, 1992) try to discriminate between three alternative interpretation (which can loosely be attributed to Arrow-Romer, Porter and Jacobs) of the growth of high-tech clusters in order to check similarities and differences with the "classical" definition of industrial districts.

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1. INTRODUCTION

The aim of this paper is to present a collection of empirical analyses which have been performed in order to verify a number of theoretical hypotheses, stylised facts and logical conjectures on the location process of high-tech firms and the development path of high-tech industrial clusters. Because of the multifaceted nature of the issue at study, different empirical exercises have been performed and are summarised in the concluding section of the paper.

The existing empirical literature has mainly focused its attention on the identification of a list of the most relevant locational factors, while relatively few contributes, which are quoted in this paper, have analysed the dynamic of clusters' development and its relations with the individual firm's location decision.

The empirical analysis is organised as follows: we first investigate (section 2) the role of geographical benefits as determinants of the industrial high-tech specialisation of an area, we then move (section 3) to the analysis of scale versus agglomeration economies for explaining the clustering of innovative activities, we further analyse (section 4) the effects of inter-industry and inter-regional relations in the dynamic of innovative industrial cluster and, finally, we test (section 5) three alternative explanations for the growth of high-tech clusters.

Several reference to the theoretical literature are explicitly quoted in the appropriate sections of this paper; however it is perhaps worth stressing that section 2 displays an empirical analysis in the tradition of classical location theory (and in particular of the least coast approach). Section 3 may be considered as an empirical test of both Krugman's and Arthur's approach to industrial location. Section 4 builds an encompassing empirical framework able to test some hypotheses put forward by the industrial geography approach, the informational cascades approach and, obviously, by the ecological approach. Section 5 is explicitly devoted to discriminate between three alternative explanations: the first which may be ascribed to Krugman, the second to Porter and the third to Jacobs.

2. THE ROLE OF GEOGRAPHICAL BENEFITS

Even though throughout the paper locational benefits have been assumed to be composed of two parts - geographical benefits, which derive from the intrinsic quality of the site in terms of inputs and infrastructures endowment and costs, and agglomeration benefits, which derive from the location of other firms in the same site - in most of the modelling framework and in the discussion of policy implications, our emphasis is always on the firm dependent part of locational benefits.

However, many empirical contributions and the practice of day-by-day industrial policy, are focused mainly, if not entirely, on the role played by geographic benefits in influencing firms location decision to accomplish a desired social and economic target (in terms of income, employment, or growth rate of the local economic system).

For this reason we decided to estimate a small number of empirical models which try to assess the relative relevance of different "location factors" in determining the location of high-tech firms and, indirectly, the development of local industrial clusters.

These models generally suffer from a very poor theoretical background. On the one hand, many dependent variables which are used in the regression equations may well be influenced by firms' entry dynamics, thus introducing a problem of endogeneity; on the other hand, such empirical specifications do not take into account the interaction which may exist between the contemporary development of different regions and industries, thus introducing a problem of mispecification.

Nevertheless we used part of our original data-set and supplemented it with other statistical sources in order to relate the location decision of high-tech firms to “objective characteristics” of US States through cross-section and panel data estimations.

The variables used in the analysis are the following:

Dependent variables

$EMPOP_{st}$ = level of employment in high-tech sectors in State *s* at time *t*

$ESTAPOP_{st}$ = number of high-tech establishments in State *s* at time *t*

$GEMPOP_{s}$ = growth rate of employment in high-tech sectors in State *s* (1986-1993)

$GESTAPOP_{s}$ = growth rate of high-tech establishments in State *s* (1986-1993)

$RELEMP_{st}$ = proportion of high-tech employment on total manufacturing employment in State *s* at time *t*

$RELESTA_{st}$ = proportion of high-tech establishments on total number of manufacturing establishment in State *s* at time *t*

Independent variables[1]

$APAY_{st}$ = individual worker’s average annual pay in State *s* at time *t*

$UNION_{st}$ = unionisation rate of the labour force in State *s* at time *t*

$UNEMP_{st}$ = unemployment rate in State *s* at time *t*

$MALEPT_{st}$ = male participation rate to labour market in State *s* at time *t*

$ECOL_{st}$ = enrolment rate in college in State *s* at time *t*

TRD_{st} = total amount of R&D expenditure in State *s* at time *t*

PAT_{st} = number of issued patent in State *s* at time *t*

HW_{st} = miles of highway in State *s* at time *t*

$FAIL_{st}$ = business failure rate in State *s* at time *t*

$INCO_{st}$ = average per capita income in State *s* at time *t*

$EXPO_{st}$ = export rate on total sales in State *s* at time *t*

$METRO_{st}$ = rate of population living in metropolitan areas in State *s* at time *t*

TAX_{st} = corporate income tax marginal rate in State *s* at time *t*

POP_{st} = level of resident population in State *s* at time *t*

2.1. ESTIMATING THE ROLE OF GEOGRAPHICAL BENEFITS IN DETERMINING LOCATION DECISIONS

[1] We collected data on other variables (on female participation in the labour market, number of colleges, university R&D). However, in order to avoid multicollinearity problems, we selected a sub-sample of variables which were more significantly related to the dependent variables. All variables have been used in two different ways: for the cross-section analyses they have been normalised with the population level; while for the panel-data estimations the have been used in absolute levels. For this reason in panel data analyses, population is used as a regressor.

The first model which has been estimated reflects the simplest possible explanation for a location process determined by geographical factors. For each time period (1986 and 1993) we run a separate regression.

$$XPOP_s = a + bAPAY_s + cUNION_s + dUNEMP_s + eMALEPT_s + fECOL_s + gTRD_s +$$
$$+ hPAT_s + iHWAY_s + lFAIL_s + mINCO_s + nEXPO_s + oMETRO + pTAX_s + e_s$$

(1)

where s stand for the State, $XPOP_s$ = $ESTAPOP_s$ in models 1 and 3 and $XPOP_s$ = $EMPOP_s$ in model 2 and 4; and ε_s is a white noise error term, assumed well behaved.

The estimated results presented in table 1, which are relatively stable for 1986 and 1993, underline the fact that few locational factors are actually relevant for the location of high-tech firms[2].

Table 1. Geographical factors explaining the location decision of US high-tech firms (cross-section analyses for 1986 and 1993)

model	1	2	3	4
year	1896	1896	1993	1993
dependent variable	estapop	empop	estapop	empop
constant	-0.130	14.625	-2.930	-6.149
t-ratio	*-0.08*	*0.48*	*-1.46*	*-0.23*
APAY	-0.006	-0.080	-0.008**	-0.038
t-ratio	*-1.18*	*-0.76*	*-1.77*	*-0.68*
UNION	-0.009*	-0.113	-0.016	-0.093
t-ratio	*-1.89*	*-1.16*	*-1.34*	*-0.61*
UNEMP	0.002	-1.116	0.120	-0.732
t-ratio	*0.04*	*-1.31*	*1.98*	*-0.92*
MALEPT	-0.009	-0.095	0.022	0.135
t-ratio	*-0.34*	*-0.23*	*0.81*	*0.39*
ECOL	10.190	115.398	10.425**	-23.251
t-ratio	*1.57*	*0.90*	*1.67*	*-0.29*
TRD	-0.090	0.204	-0.194	-1.060
t-ratio	*-0.59*	*0.06*	*-1.20*	*-0.50*
PAT	2.0865*	31.642*	2.2445*	21.2408*
t-ratio	*3.39*	*2.59*	*4.02*	*2.91*
HWAY	-0.036	-0.222	-0.049	0.695
t-ratio	*-1.48*	*-0.46*	*-0.98*	*1.06*
FAIL	-0.042	6.894	0.322	32.804
t-ratio	*-0.14*	*1.15*	*1.49*	*11.64*
INCO	-0.010**	-0.003	-0.011**	-0.003
t-ratio	*-1.67*	*-0.02*	*-2.35*	*-0.05*
EXPO	0.015	0.64298*	0.002	0.29482*
t-ratio	*1.18*	*2.58*	*0.15*	*2.09*
TAX	0.006**	0.139	-0.009	-0.074
t-ratio	*0.35*	*0.42*	*-0.48*	*-0.31*
METRO	0.006	0.069	0.005	0.008
t-ratio	*1.83*	*1.10*	*1.44*	*0.16*
Adj. R sq.	0.61	0.45	0.50	0.79
n. of obs.	51	51	51	51

[2] All usual diagnostic tests have been performed on these rather unstructured and simple regressions, enabling us to reject any significant deviation from the classical model. The use of population as a weighting criterion allows us to eliminate the heteroskedasticity problem which may be generated by the size difference between US States.

* = 5%, ** = 10% l.o.s.

In particular, when clustering is measured through the number of establishments, the patent variable display a positive and significant coefficient at the 5% l.o.s.[3] and the per-capita income display a negative and significant coefficient; while, when the measured variable is the level of employment, patents play the same role and exports, with a positive and significant coefficient, take the place of per-capita income[4]. While the positive correlation with the patent variable has an intuitive explanation - high-tech firms want to locate in highly innovative areas (as measured by the number of per-capita patents) - the negative correlation with the income variable seems rather odd. However, if one think that innovative firms may well look for green-field location far from established production centres (which are still based on traditional industries) and far from metropolitan congestion, then the sign of the correlation may easily be explained.

We tried also to add some temporal dimension to these simple regressions, by using, as dependent variables, firstly the growth rate of $ESTAPOP_{st}$ and $EMPOP_{st}$ ($GESTAPOP_{st}$ and $GEMPOP_{st}$); secondly, by regressing the 1993 values of the dependent variables on the 1986 values of the dependent ones. However these two empirical estimates do not give any valuable results. We decide, therefore, to exploit both the cross-sectoral and the time-series dimension of this data-set and we estimated the following panel data regression equation.

$$RELX_{st} = a + bAPAY_{st} + cUNION_{st} + dUNEMP_{st} + eMALEPT_{st} + fECOL_{st} +$$
$$+ gTRD_{st} + hPAT_{st} + iHWAY_{st} + lFAIL_{st} + mINCO_{st} + nEXPO_{st} + pTAX_{st} + e_{st}$$

(2)

where, following the notation used above, s stands for the State, $RELX_{st} = RELESTA_{st}$ in models 1r and 1f, and $RELX_{st} = RELEMP_{st}$ in model 2r and 2f, and e_{st} is a white noise error term, assumed well behaved.

We estimated two different regressions, the first where the industrial specialisation of the State is measured in term of establishments and the second where it is measured in term of employment. Both equations have been estimated by considering individual effects to be either random or fixed. Table 2 shows the results:

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[3] For the regression on the 1986 data, the unionisation rate displays a significant and negative coefficient showing that high-tech firms, when choosing their location, look for easier industrial relations environments. The rate of metropolitan population displays a positive and significant (at 10% l.o.s.) coefficient too, signalling an influence of urbanisation economies.

[4] For the regression on 1993 data, the failure rate displays a significant and positive coefficient, showing that dynamic areas where firms turnover rate is higher than average, may encourage firms entry (possibly it is seen as a signal of low exit costs). At 10% l.o.s. the worker’s average annual pay displays a significant negative coefficient; while the enrolment in college display a significant and positive coefficient.

Table 2. Location factors for US high-tech firms (panel data estimation)

models	1r		1f		2r		2f	
	random effects		fixed effects		random effects		fixed effects	
dependent variables	RELESTA		RELESTA		RELEMP		RELEMP	
independent variables	coefficients	*z*	coefficients	*t*	coefficients	*z*	coefficients	*t*
APAY	-1.865	*-0.443*	-11.256**	*-1.895*	-48.864	*-0.691*	-78.8	*-0.415*
UNION	10.435	*1.164*	18.488	*1.194*	-267.731	*-1.439*	9.722	*0.032*
UNEMEP	0.0664	*0.002*	65.483	*1.548*	-4161.789*	*-4.672*	-3294.324*	*-2.435*
MALEPT	15.976	*0.455*	-23.269	*-0.667*	-114.07	*-0.175*	680.644	*0.61*
ECOL	6.625*	*2.037*	8.901*	*2.009*	26.734	*0.587*	120.3	*0.849*
TRD	-0.000805	*-0.01*	0.0399	*0.465*	-0.253	*-0.188*	0.405	*0.147*
PAT	0.796*	*2.206*	0.132	*0.336*	13.126*	*2.095*	5.53	*0.441*
INCO	-0.00138*	*-3.595*	-0.000552	*-0.991*	-0.0158*	*-2.125*	-0.0104	*-0.586*
METRO	0.00528**	*1.649*	-0.00338	*-0.649*	-0.00602	*-0.145*	-0.0203	*-0.122*
EXPO	-4.959	*-0.245*	2.43	*0.108*	991.524*	*3.053*	577.069	*0.805*
TAX	-24.135	*-0.616*	-103.637*	*-2.261*	646.761	*1.075*	128.242	*0.087*
HWAY	1.845	*0.072*	-20.799	*-0.688*	74.402	*0.151*	-28.799	*-0.03*
FAIL	-116.188	*-0.512*	-175.249	*-0.87*	57202.83*	*10.289*	54149.08*	*8.405*
D93	681.922	*2.288*	1173.46*	*3.203*	-10857.77*	*-2.014*	-5218.995	*-0.445*
POP	-0.701*	*-2.40*	-0.208	*-0.35*	-0.341	*-0.086*	-6.928	*-0.365*
constant	1828.086	*0.668*	6693.506*	*2.336*	42974.73	*0.839*	1774.83	*0.019*
Adj. R sq.	0.37		0.37		0.60		0.22	
F test			6.59	*F(15, 36)*			5.86	*F(15, 36)*
Hausman test	15.77	*Chi2(15)*			14.92	*Chi2(15)*		
Breusch-Pagan test	24.91	*Chi2(1)*			18.16	*Chi2(1)*		
number of observations: 102								

* = 5%, ** = 10% l.o.s.

The F tests show that individual effects are relevant, Hausman specification tests indicate that these individual effects should be model as fixed rather than random. As far as the industrial specialisation of States measured in term of high-tech establishments is concerned, when individual effects are treated as random, college enrolment, number of patents (and the dummy variable for 1993, *D93*) show significant and positive coefficients, while population and per-capita income have significant but negative coefficients confirming that the presence of an educated labour force and innovative structures are important location factors for high-tech firms. When individual effects are treated as fixed, population becomes insignificant (since this source of inter-state variance is captured by the model's specification), the quality of the local labour force stays significant and positive and the tax coefficient appears to be significant with a negative coefficient. The worker's average annual pay records a negative coefficient (which is significant at the 10% l.o.s.)

When high-tech employment is the dependent variable for detecting State industrial specialisation (using random effects), the number of issued patents, the export rate and business failure rate show significant and positive coefficients, while the unemployment rate has a negative coefficient. The use of a fixed effects specification results in only two significant coefficients (business failure and unemployment rate). These results indicate that an innovative, dynamic and internationally competitive environment is the best location for high-tech industries, while declining industrial areas are the worst.

3. CLUSTERING OF FIRMS OR WORKERS? SCALE VS. AGGLOMERATION ECONOMIES

Recent papers (e.g. Brülhart - Thorstensson, 1996; Davis - Weinstein, 1996; Dumais et al., 1997; Kim, 1997; Ellison - Glaeser, 1997; Rombaldoni - Zazzaro, 1997; Greenaway - Torstensson, 1998) have thoroughly discussed the phenomenon of firms location and regional specialisation both from a theoretical and an empirical perspective.

Classical location theory considers the firm's location decision as a spatial optimisation problem where the spatial distribution of inputs is considered as given and the only strategic element refers to the behaviour of the other firms. Recent theoretical contributions have instead shown that firms' locations and, consequently, regional specialisation patterns are caused by the interplay of the location decisions of firms and workers. In other words if classical location theory can be summarised in the claim "geography matters" - in the sense that the exogenous spatial distribution of inputs (and, sometimes, consumers) crucially determines firms' location decisions -; more recent approaches seem to state that "history, and expectations", matter most.

If this is the case, then the explanation of firms location decision could be found, without referring to exogenously determined locational factors, within the actual firms locational patterns. Krugman (1991a and 1991b) - referring explicitly to Marshall (1920) - stresses the role of economies of scale (which are internal to the individual firm) as the main centripetal force determining firms'[5] location; while other authors (Scott, 1986; Arthur, 1990; Becattini, 1998; Storper -Walker, 1984) - quoting almost the same passages from Marshall (1920) - identify agglomeration economies (which are external to the individual firm) as the key determinants of industrial clustering.

The contrast is extended also to the interactions between scale and agglomeration economies. According to Krugman, economies of scale are a pre-condition to the existence of agglomeration economies[6] (thus these two factors coexist and, in general, they are mutually re-enforcing). On the contrary, according to Scott (1986) the very trade-off which exists between agglomeration and scale economies can explain why, in certain industrial sectors and in certain areas, large firms prevail; while in other industries and/or locations, small interdependent firms seem to be the general rule[7].

Thus the recent empirical literature (Henderson, 1994; Kim, 1995 and 1997; Hanson, 1996; Brülhart - Thorstensson, 1996; Ellison - Glaeser, 1997, Geroski et al., 1998 von Hagen - Hammond, 1998) has mainly tested the relative importance (among other factors[8]) of scale and agglomeration economies in determining the existence of increasing returns to locations and, indirectly, the emergence of industrial clusters. It is therefore interesting to analyse in greater detail the role played by internal and external economies in determining the geographical distribution of high-tech industries.

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[5] The other centrifugal forces in his models are transport costs and the share of immobile agricultural workers.

[6] "If each firm could produce in both locations (...), then the full portfolio of firms and workers could be replicated in each location and the motivation for localisation would be gone" (Krugman, 1991a, p. 40-41).

[7] "Vertical disintegration encourages agglomeration and agglomeration encourages vertical disintegration" (Scott, 1986, p. 224).

[8] Kim (1997), for example, stresses the relevance of the location of raw materials and natural advantages.

3.1. A ROUGH INDICATOR

A first technique implies the use of a rough indicator of the relevance of agglomeration versus scale economies which, for each sector, is calculated as the difference between the value of the concentration or inequality indexes referring to establishments and those referring to employment. When the difference is positive (i.e. the sector is more spatially concentrated in terms of establishment) we may say that agglomeration economies are prevailing; when the difference is negative (i.e. the sectors displays a higher concentration index on employment than on establishments) scale economies may well be the stronger engine of clustering dynamics. This procedure can be implemented for each inequality and concentration index. We have therefore built a general index for each industry, as shown in tables 6.3 and 6.4, adding up the values of all indexes.

Table 3. Agglomeration versus scale economies at FLA level

Industries	*USA*	*UK*	*FRA*	*ITA*
170	-1.39		-0.67	**0.21**
244	-0.70	-0.06	-0.77	-1.25
300	-0.19	-0.12	-0.86	-2.72
321	0.00	**0.03**	-1.29	-0.40
331	-0.20	**0.02**	-	-0.65
332	-0.22	-0.03	-	-1.03
333	-0.44	**0.01**	-	-0.21
334	-2.33	-0.09	-	-1.62
330	-	-	-0.67	-
340	-1.36	-	-0.78	-2.77
353	-0.82	-0.08	-0.73	-1.79
total h-t	-0.07	**0.02**	**0.09**	-1.81
D	**0.15**	**0.00**	-0.95	-0.40

Table 4. Agglomeration versus scale economies at SLA level

Industries	*USA*	*UK*	*FRA*	*ITA*
170	-1.53	-	-0.01	-0.01
244	-0.63	**0.01**	-0.07	-0.10
300	-0.04	-0.05	-0.13	-0.32
321	**0.10**	**0.17**	-0.03	**0.02**
331	**0.05**	**0.05**	-	-0.11
332	**0.03**	-0.02	-	-0.09
333	**0.09**	**0.36**	-	**0.25**
334	-1.47	**0.04**	-	-0.16
330	-	-	**0.05**	-
340	-1.57	-	**0.04**	-0.14
353	-0.70	**0.12**	-0.03	-0.08
total h-t	**0.03**	**0.02**	-0.03	-0.13
D	-0.12	**0.08**	**0.06**	-0.06

According to these tables, agglomeration economies seem to play a major role at SLA than at FLA level. However some industry-specific features can be summarised as follows. Agglomeration economies play a major role in the Electronic components industry (321), and in the Instruments sector (330) (with specific reference to Medical and surgical instruments (331), and to Industrial process control instruments (333)); while scale economies are prevailing in the Textiles industry (170) (the only notable exception being Italy, at the FLA level because of the relevance of "industrial districts"), Motor vehicles (340) (here is France at the SLA level which display a surprising result), and Optical and photographic equipment (334). When the high-tech sectors are considered as one single industry the results are somehow blurred and seem to be more influenced by national and institutional factors. These tables in fact show some interesting country-specific differences. In particular it seems that, while in some countries (such as the US and the UK[9]), a prominent role in high-tech sectors is played by small firms, in other countries (such as France and Italy), high-tech sectors are still characterised by large size, sometimes publicly owned, firms. The relevance of these results must however not be overstated, since inter-countries differences may have been exacerbated by the rough aggregation of different inequality and concentration indexes.

It is therefore useful to follow the works of Kim (1995 and 1997) and Rombaldoni - Zazzaro (1997), integrating and modifying the approach used by these authors, in order to take into account three other phenomena which play a crucial role in shaping the development of high-tech clusters: the existence of non linearities (i.e. the existence of diseconomies), the presence of inter-industry linkages, and the role of geographical spillovers and locational shadowing.

3.2. A MODEL

The aim of this empirical exercise is to test the relative importance of scale versus agglomeration economies in determining industrial clusters. What we want to test is a general relation which explains the spatial concentration of an industry *i* in region *r* in terms of scale, agglomeration and other relevant variables. Formally

$$spatial\ concentration_{ir} = f\left(scale_{ir}\ ,\ aggl._{ir}\ ,\ other_{is}\right)$$

(3)

In principle, there are no *a-priori* reasons for choosing one particular functional form for the regression equation. However if one refers back to section 3, where the issue of whether these two forces are complementary or substitutes is discussed, it becomes clear that, by choosing a simple additive functional form, we implicitly assume that agglomeration and scale economies are substitutes. On the other hand, by choosing a multiplicative functional form, we implicitly assume that they are complementary. Even though we had an *a-priori* weak preference for the complementarity version of the story, we let the data speak for themselves and we ended up choosing a multiplicative functional form[10] which gave better results on the Ramsey RESET test for functional mispecification.

We enlarged the original model of Rambaldoni and Zazzaro in order to include other relevant forces which can explain the emergence of industrial clustering, namely: geographical and industrial spillovers. In particular we modelled geographical spillovers as the effects caused by the industrial specialisation of a larger area (i.e. a SLA for a FLA), and industrial spillovers as the effects caused by the specialisation of the area in other high-tech sectors. We also tried to take into account the role played by non linearities in agglomeration and scale economies, to explain why firms and cluster do not grow infinitely.

The variables which have been used (with few algebraic transformations) in the regressions are the following:

Dependent variable:

LQM_{iF} = index of industrial specialisation, calculated as the employment location quotient for industry *i* in FLA *F*). The employment location quotient has been chosen between various candidates, as the index for industrial specialisation, because it takes into account the size differences

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[9] Even if it must be recalled that, because of confidentiality reasons employment data for UK were almost unavailable. Therefore the index for UK has been constructed only on the basis of the spatial concentration ratio which, in general, seems to overestimate the effects of agglomeration economies.

[10] Which can be linearly estimated through a simple double-log transformation.

which exist among different establishments, different FLAs and the relative industrial structure of different countries.

Independent variables:

SC_{iF} = index of economies of scale (calculated as the ratio between the employment and the number of establishments in industry *i* and in FLA *F*). The chosen variable is therefore the industry and region specific average size of establishment.

AG_{iF} = index of economies of agglomeration (calculated as the ratio between the number of establishments in industry *i* and in FLA *F* and the number of manufacturing establishment in the country). The chosen variable weights the number of industry- and region-specific establishments with the number of manufacturing establishment in a given country.

$RLQM_{iS}$ = index of geographical spillovers (calculated as the employment location quotient for industry *i* in the higher geographical level SLA *S*, with the exclusion of the FLA under analysis). The chosen variable, in principle, would allow one to identify both positive and negative effects (locational shadowing) which derive from the industrial specialisation of the surrounding areas[11].

$LQMHT_{iF}$ = inter-industry-linkages (calculated as the employment location quotient for the other high-tech sectors - i.e. excluding industry *i* - in FLA *F*). This variable measures the extent of inter-industry spillovers which are assumed to be more relevant within the group of high-tech industries.

For each industry *i*, the estimated model is therefore multiplicative and becomes additive in the double logarithmic specification:

$$LLQM_{iF} = a + bLSC_{iF} + cLAG_{iF} + dLRLQM_{iS} + eLLQMHT_{iF} + h_{iF}$$
(4)

where all variables are in logs and h_{iF} is a white noise error term, assumed well behaved.

We further tested for the existence of non linearities (i.e. of scale and agglomeration diseconomies after a certain threshold) by introducing two further variables, these being the square of the scale and of the agglomeration indexes. The best results were obtained in the linear additive specifications, where almost all squared coefficients had the expected negative sign and were significantly different from zero. However these specifications had to be rejected on the base of failed tests for mispecification based on the normality of residuals[12].

3.3. THE DATA

In order to estimate the relative importance of scale versus agglomeration economies we used part of the original dataset to estimate six industries specific cross-section versions of equation 2. based on first level areas (FLA) for 4 countries.

For reasons of international comparison we restricted our analysis to 5 sectors: 244 (Pharmaceutical), 300 (Computers and office equipment), 321 (Electronic components), 330 (Instruments), 353 (Aerospace), plus a macro-sector HT (total high-tech) which is the sum of all previously quoted ones.

The chosen functional form requires all variables to be strictly positive. We thus faced the alternatives of either dropping the observations where variables were equal to zero (introducing a

[11] A better indicator for such a phenomenon would have been the relative specialisation of the bordering geographical FLAs. However the use of SLA is justified in terms of computational convenience and in terms of the hierarchical decision methods used by managers when taking location decisions (as reported by Premus, 1982).

[12] For these regressions no results will therefore be reported.

sample bias) or substituting the zeros in the data-set with a small value marking these observations with dependent dummy variables. Although the second alternative seems neater we chose to drop the zero-variables observations because of the very nature of the variables. Each time the LQM_{if} is equal to zero, SC_{if} and AG_{if} are also equal to zero, because when in a FLA there are no establishments in a certain industry, there are no employees too.

Because of the nature of the data[13], and the chosen variables and functional form, we were thus unable to use all 306 observations available at the FLA level in our dataset. Each industry specific cross-section regression has therefore been estimated on a specific subset whose size spanned from a maximum of 255 (for the total high-tech sector) to a minimum of 162 (for the Aerospace industry) observations.

3.4. THE RESULTS

Table 5 summarises the result of six industry-specific regressions. In general scale economies seem to prevail over agglomeration economies (the scale parameters are about 5 time larger[14]), the exception being sectors 330 and the HT (where agglomeration parameters are, respectively, 3 and 1.5 times larger)[15].

Table 5. Scale versus agglomeration economies in the location of high-tech firms

	244	*300#*	*321#*	*330*	*353*	*HT*
	Pharmaceut.	*Computers*	*E'tronics*	*Instruments*	*Aerospace*	*high-tech*
constant	-3.86	-4.37	-2.43	-0.45	-4.18	-0.76
t-ratio	*-1639.00*	*-25.57*	*-11.83*	*-3.81*	*-11.50*	*-6.14*
LSC_{if}	0.95	0.82	0.51	0.11	0.81	0.17
t-ratio	*22.12*	*17.94*	*10.88*	*3.63*	*14.56*	*5.21*
LAG_{if}	0.20	0.13	0.03	0.34	0.17	0.27
t-ratio	*5.06*	*4.01*	*1.07*	*9.54*	*3.17*	*7.41*
$LLQMHT_{if}$	0.30	0.49	0.56	0.35	0.53	-
t-ratio	*5.21*	*6.03*	*8.77*	*5.83*	*5.16*	-
$LRLQM_{if}$	0.21	0.17	0.36	-0.10	0.16	0.56
t-ratio	*3.95*	*3.43*	*5.20*	*-2.11*	*1.89*	*7.76*
Adj. R sq.	0.85	0.79	0.73	0.58	0.77	0.52
n. of obs.	214	204	239	247	162	255

# indicates that regression parameters have been estimated using White's corrected version of the variance-covariance matrix of parameters; **-** signals that industrial spillovers could not be calculated for total high-tech. All coefficients of regressions are significant at the 5% l.o.s. (except $LRQM_{if}$ for Aerospace (353) which is significant only at 10% l.o.s.).

R^2 for the specific sectors are always very high (spanning from 0.73 to 0.85) while for sectors 330 and HT the values are lower (between 0.52 and 0.58) although still significantly high for cross-section analyses. All regression equations have been tested for functional form mispecification (Ramsey RESET test), non normality of residuals (skewness and kurtosis of residuals), heteroskedasticity (Breusch and Pagan test), and multicollinearity (correlation ratios between

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[13] For a great majority of the UK counties data on sectoral employment have been withheld by the ONS for confidentiality reasons.

[14] In the Electronic components industry, the agglomeration economies parameters is not significantly different from zero, therefore this ratio cannot be calculated.

[15] The results for HT are heavily influenced by the Instruments industry. This is due to the fact that this industry, which is characterised by a low average firm size, records the largest proportion of the total number of firms in high technology industries (64% of the total data-set).

dependent variables and auxiliary regressions) and no deviation from the classical model could be detected, apart from a slight heteroskedasticity for industries 300 and 321 which has been corrected by using White's procedure.

It is interesting to note that scale economies seem to perform a larger role in Pharmaceuticals (this is consistent with the structure of the industry where larger plants prevail), while agglomeration economies largely contribute to the geographical concentration of the Instrument industry (where customised production and tailor made products are the rule)[16]. In absolute terms, scale economies are very relevant also for Computers and office machinery and Aerospace. In relative terms, for the Electronic components industry, while scale economies effects are not as important as in other high-tech sectors, agglomeration economies play an absolutely insignificant role in determining the industrial specialisation of the area. However when the complex of all high-tech sectors is being considered, then the agglomeration economies seem, on average, to be more important than scale economies.

By using a double log specification, regression parameters can be interpreted as elasticities. In the Pharmaceutical industry, therefore, a 1% increase of the average establishment size causes an 0.95% increase in the industry location quotient, while the same amount of increase in the relative number of establishments raise the industry's location quotient by a mere 0.2%. It is also worth noting that none of the parameters is higher than the unity.

A further remark concerns the relevance of inter-industry linkages. All the regression equations record a positive coefficient for this variable even if this phenomenon appears to be stronger in the Electronic components and in the Aerospace industries, which are benefiting more from the closeness to other high-tech sectors. One can explain this result in term of strong forward linkages for Electronic components (whose products are inputs in several high-tech industries) and of backward linkages for Aerospace (which uses, as inputs, several products of other high-tech sectors).

The final test concerns the presence of spatial positive spillovers or the emergence of locational shadowing. For all but one sector $LRLQM_{iS}$ displays a positive and significant coefficient signalling that a positive relation exists between the FLA specialisation in an industry and the specialisation of the corresponding SLA. Instruments industry displays the existence of locational shadowing phenomena, while and Aerospace records such a low (even though positive) value of the geographical spillovers coefficients and of the relative t-ratio, that one would infer the inexistence of any role played by geographical spillovers, both in positive and negative terms.

4. THE GROWTH OF AN ISOLATED CLUSTER

If the set of potential entrants for one specific cluster were independent and separated (had no overlap) from the sets of potential entrants relative to other clusters, then the easiest estimation procedure for analysing the development path of a cluster would imply the estimation of equation (5)

$$\frac{dn_q(t)}{dt} = r_q n_q(t)\left(1 - \frac{n_q(t)}{K_q}\right)$$

(5)

however, such formulation obliges one to determine an exogenous value for the maximum dimension of the cluster (K_q).

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[16] One must also consider that Instruments industry (especially in Italy and France) includes many different sub-sectors whose technological level (in certain countries) is not very high.

An alternative formulation allows one to overcome such limitations. In this way it is possible to express the rate of variation of the cluster industrial mass as a function of the number of incumbents without any exogenously determined parameter.

$$\frac{dn_q(t)}{dt} = an_q(t) + b\left(n_q(t)\right)^2$$

(6)

Referring to equation (5), $a = r_q$, the incipient rate of growth and $\frac{a}{b} = K_q$ the maximum dimension of the cluster.

One could then estimate an empirical version of equation (6) as follows

$$\frac{dn_q(t)}{dt} = an_q(t) + b\left(n_q(t)\right)^2 + e_q(t)$$

(7)

where $e_q(t)$ is a white noise error term, assumed well behaved, to obtain the estimated coefficients for K_q and r_q.

Once these estimated coefficients have been obtained, one would use them in a regression where the incipient rate of growth and the maximum dimension of the population are functions of a series of locational factors.

In particular, by using the variables' description of section 2, one would estimate the following regression equations for each industrial cluster *q* (i.e. for the industry *i* in State *s*)

$$K_{is} = a + bPOP_{is} + cLAND_{is} + dUNEMP_{is} + eMALEPT_{is} + fMANUF_{is} + gTRD_{is} +$$
$$+ hPAT_{is} + iHWAY_{is} + lECOL_{is} + mINCO_{is} + nEXPO_{is} + pTAX_{is} + e_{is}$$

(8)

where the variables used as regressors in (6.8) measure the endowment of input and infrastructures, which are crucial to the development of high-tech businesses and e_{is} is a white noise error term, assumed well behaved.

$$r_{is} = a + b\frac{HT_{is}}{MANUF_{is}} + cMETRO_{is} + dUNION_{is} + eECOL_{is} + fFAIL_{is} +$$
$$+ gTRD_{is} + nEXPO_{is} + pTAX_{is} + e_{is}$$

(9)

where the variables used as regressors in (6.9) measure the ability to attract outsiders and generate new high-tech firms and e_{is} is a white noise error term, assumed well behaved.

However, since we believe that the development of a high-tech cluster is heavily dependent on the external conditions (and in particular on what is happening in other industries within the same region and in other regions within the same industry), we are convinced that such models would give biased and inefficient estimates. A possible way round this problem is the estimation of interaction models which can take into account inter-industries and inter-region dynamics.

5. COMPETITION AND CO-OPERATION IN THE DYNAMIC OF CLUSTERS DEVELOPMENT

According to this approach, the development path of a cluster, which is determined by firms' location decision, can be entirely represented by the interactions which exist between entrants and incumbents in different regions and industries. All pure locational factors are assumed to be either mobile or substituted by the developing industries which, in the words of Storper - Walker (1989) are capable of "producing regions".

5.1. A MODEL

The analytical formulation of these interactions when the number of interacting entities is equal to 2 is as follows:

$$\begin{cases} \dfrac{dn_r}{dt} = \left(a_r - a_{rr}n_r - a_{rs}n_s\right)n_r \\ \dfrac{dn_s}{dt} = \left(a_s - a_{ss}n_s - a_{sr}n_r\right)n_s \end{cases} \tag{10}$$

where n_r and n_s are the "economic masses" (number of incumbents) in region r and s; a_r and a_s are the intrinsic rates of increase of each region in isolation; a_{rr} and a_{ss} are the intra-regional competition parameters which reflect the inhibiting effects that a firm's entry has on the growth rate of the same region (because of congestion effects); a_{rs} and a_{sr} (inter-regional competition parameters) show the inhibiting effects that one firm, locating in a region, has on the growth of the other region (inter-regional competition parameters).

One then would like also to take into account the inter-industry interactions which develop within the same region. If this is the case, then a two-regions, two sectors can be modelled as follows

$$\begin{cases} \dfrac{dn_r^i}{dt} = \left(a_r^i - a_{rr}^i n_r^i - a_{rs}^i n_s^i + a_r^j n_r^j\right)n_r^i \\ \dfrac{dn_s^i}{dt} = \left(a_s^i - a_{ss}^i n_s^i - a_{sr}^i n_r^i + a_s^j n_s^j\right)n_s^i \\ \dfrac{dn_r^j}{dt} = \left(a_r^j - a_{rr}^j n_r^j - a_{rs}^j n_s^j + a_r^i n_r^i\right)n_r^j \\ \dfrac{dn_s^j}{dt} = \left(a_s^j - a_{ss}^j n_s^j - a_{sr}^j n_r^j + a_s^i n_s^i\right)n_s^j \end{cases} \tag{11}$$

where the subscript r, s refer to regions, and the superscripts i, j refer to industries.

It appears evident that, even though this formulation is linear, and expresses the agglomeration diseconomies without exogenously determined parameters, its applicability is limited by the large number of parameters which have to be estimated. We thus proceeded by regressing the growth of each cluster (i.e. for the couplet industry-region) on the different interaction coefficients (these being both inter-regional and inter-sectoral). The results of these regressions were disappointing: in many cases the inner dynamics of the cluster growth (which are represented by the first two dependent variables in equation 11) explained a large part of the variance of $\dfrac{dn_r^i}{dt}$, while the other estimated interaction coefficients were almost always insignificant.

Table 6 reports the only valuable results which we were able to extract from a set of over 50 regressions and refers only to inter-state intra-industry relations.

Table 6. US high-tech cluster development and inter-state competition coefficients

cluster growth	period of time	cluster size	squared cluster size	first competitor	second competitor	third competitor	fourth competitor	Adj. Rsq
CAL357	1957-1994			TEX357				0.66
		0.254*	-0.00016*	-0.81*				
t-ratio		*3.66*	*-2.88*	*-2.04*				
CAL367	1957-1994			PEN367	MAS367	TEX367	ILL367	0.40
		0.19*	-0.12	-1.03*	-0.85*	-0.82**	-0.52**	
t-ratio		*3.78*	*-0.4*	*-3.49*	*-3.02*	*-1.90*	*-1.96*	
CAL380	1949-1994			MAS380				0.72
		0.18**	-0.00036*	-0.31***				
t-ratio		*1.96*	*-2.58*	*-1.80*				
MAS357	1949-1994			TEX357	CAL357			0.55
		*0.21**	-0.00016	-0.24*	-0.072*			
t-ratio		*4.3*	*-0.47*	*-2.87*	*-2.11*			
MAS380	1949-1994			PEN380				0.59
		0.17*	-0.0001*	-0.11*				
		2.53	*-2.02*	*-2.18*				

* = 5%; ** = 10%; *** = 25% l.o.s.

From table 6 it appears that, as far as the Computer industry (357) is concerned, the first three States play very different roles: California is still the leading State but is beginning to suffer from the competition of Texas. Massachusetts, the old leader, is fighting directly with Texas and indirectly with California, while Texas Computer industry grows without any significant interference from other States.

In the Electronic components industry (367) the leadership of California is clear in absolute term, but in the last ten years, when California has incurred some difficulties, other states (such as Pennsylvania, Massachusetts, Texas and Illinois) have shown their competitive strength.

In the Instruments sector (380) - where New York has steadily reduced its presence and California has taken the lead - our estimates signal the existence of a competitive relation between two late-comer States (Massachussets and Pennsylvania), which are progressively catching-up.

As already said, the main difficulty with such an empirical analysis is represented by the exponential increase in the number of regressors to be estimated. The interaction variables - which refer to the number of firms in each other high-tech sector located in the same State and to the number of firms belonging to the same sector located in other States - may easily overcome the number of available observations. We found a solution to solve this problem by creating two composite variables which, for each high-tech cluster (defined as the couplet of state *s* and a sector *i*), summarise the inter-state/intra-industry relations $n_{(S-s)i}$ [17] (i.e. the number of incumbents in all but state *s* belonging to industry *i*) and the intra-state/inter-industry relations $n_{s(I-i)}$ (i.e. the number of incumbents in state *s* belonging to all but industry *i*). For each cluster we therefore estimated the following regression:

$$\frac{dn_{si}}{dt} = \alpha + \beta_1 n_{si} + \beta_2 n_{si}^2 + \beta_3 n_{(S-s)i} + \beta_4 n_{s(I-i)} + \varepsilon_{si} \qquad (12)$$

All regression equations have been tested for serial correlation (Lagrange multiplier), functional form mispecification (Ramsey RESET), non normality of residuals (skewness and kurtosis), heteroskedasticity (Breusch and Pagan), and multicollinearity (correlation ratios between dependent variables and auxiliary regressions) and no significant deviation from the classical model could be detected. Table 7 presents the results.

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17 Table 7 shows two different measurements of the inter-state/intra-industry relations. The first (absolute) measures the number of incumbents in other significant industry-specific clusters. The second (relative) measures the ratio between the above and the number of US establishments belonging to that particular high-tech industry.

Table 7. The development of clusters: inter-regional and inter-industries effects

cluster growth	period of time number of obs.	cluster size	squared cluster square	interstate intraindustry relations	interstate relative relations	intrastate interindustry relations	**Adj. Rsq**
DCAL283	1957-1994	0.40***	0.0004	149.21*		0.14*	**0.37#**
t-ratio	*38 obs.*	*-1.16*	*-0.49*	*2.24*		*3.51*	
DCAL283					161.31*		
t-ratio					*2.58*		
DCAL357	1957-1994	0.24***	-0.0002***	-0.13***		0.048	**0.44#**
t-ratio	*38 obs.*	*1.26*	*-1.64*	*-1.36*		*0.32*	
DCAL357					45.54		
t-ratio					*0.15*		
DCAL367	1959-1994	0.32	-0.0002**	-0.04		0.004	**0.22#**
t-ratio	*35 obs.*	*0.64*	*-1.92*	*-0.10*		*0.3*	
DCAL367					-1580.6***		
t-ratio					*-1.19*		
DCAL372	1957-1994	0.02	-0.0001	-0.09***		0.01*	**0.43#**
t-ratio	*38 obs.*	*0.065*	*-0.34*	*-1.60*		*2.24*	
DCAL372					254.69		
t-ratio					*0.63*		
DCAL380	1948-1994	-0.02	-0.00002	0.01		0.04	**0.68#**
t-ratio	*45 obs.*	*-0.12*	*-0.30*	*0.07*		*0.88*	
DCAL380					-527.17		
t-ratio					*0.57*		
DCAL737	1974-1994	0.08	0.00004***	-0.20		0.46	**0.64**
t-ratio	*20 obs.*	*0.74*	*1.33*	*-0.73*		*0.81*	
DCAL737					-0.24		
t-ratio					*-1.51*		
DTEX283	1957-1994	-0.81**	0.0002	0.029*		0.02*	**0.55#**
t-ratio	*38 obs.*	*-1.86*	*0.05*	*3.14*		*3.79*	
DTEX283					172.49*		
t-ratio					*4.26*		
DTEX357	1957-1994	-0.27	-0.00003	0.011		0.03**	**0.34#**
t-ratio	*38 obs.*	*-1.2*	*-0.033*	*0.97*		*1.81*	
DTEX357							
t-ratio							
DTEX367	1959-1994	-0.90*	-0.00005	0.049**		0.27*	**0.53**
t-ratio	*35 obs.*	*-2.68*	*-0.16*	*1.77*		*4.77*	
DTEX367							
t-ratio							
DTEX372	1957-1994	-0.44*	0.0001	-0.14***		0.20	**0.52#**
t-ratio	*38 obs.*	*-2.61*	*0.61*	*1.16*		*0.91*	
DTEX372					-81.09		
t-ratio					*-0.62*		
DTEX376	1974-1994	0.78*	-0.11*	-0.14		0.004*	**0.51**
t-ratio	*20 obs.*	*2.63*	*-3.33*	*-0.33*		*3.76*	
DTEX376					19.29*		
t-ratio					*2.33*		
DTEX380	1948-1994	-0.17	-0.0001	-0.002		0.097***	**0.33#**
t-ratio	*45 obs.*	*-0.48*	*-0.84*	*-0.08*		*1.26*	
DTEX380					-471.75***		
t-ratio					*-1.47*		
DTEX737	1974-1994	0.46	0.00008***	-0.17***		1.36	**0.46#**
t-ratio	*20 obs.*	*0.54*	*1.32*	*-1.43*		*1.12*	
DTEX737					-0.11*		
t-ratio					*-2.96*		
DMAS283	1957-1994	-0.35	0.0003	0.036**		0.012*	**0.44#**
t-ratio	*38 obs.*	*-0.65*	*0.047*	*1.73*		*3.24*	
DMAS283					-14.94		
t-ratio					*-0.32*		
DMAS357	1957-1994	0.35*	-0.002*	0.09*		0.053*	**0.49#**
t-ratio	*38 obs.*	*2.08*	*-2.72*	*2.12*		*2.09*	
DMAS357							
t-ratio							

Table 7. continues

cluster growth	period of time number of obs.	cluster size	squared cluster size	interstate intraindustry relations	interstate relative relations	intrastate interindustry relations	**Adj. Rsq**
DMAS367	1959-1994	-0.16	-0.0004	-0.00009		0.18**	**0.05**
t-ratio	*35 obs.*	*-0.54*	*-0.89*	*0.0023*		*1.54*	
DMAS367					-309.05		
t-ratio					*0.59*		
DMAS376	1974-1994	-0.33	0.04	-0.021		0.002*	**0.57#**
t-ratio	*20 obs.*	*-0.65*	*0.51*	*-0.56*		*2.25*	
DMAS376							
t-ratio							
DMAS380	1948-1994	-0.54	-0.0003**	-0.029		0.033	**0.38#**
t-ratio	*45 obs.*	*-0.26*	*-1.95*	*-1.12*		*0.82*	
DMAS380					-316.68***		
t-ratio					*-1.16*		
DNYO283	1957-1994	-0.73*	0.0019*	-0.058*		0.039	**0.33**
t-ratio	*38 obs.*	*-2.69*	*2.47*	*-2.13*		*2.23*	
DNYO283					-123.92***		
t-ratio					*-1.31*		
DNYO737	1974-1994	-1.02**	-0.00008	0.26*		-0.25	**0.36**
t-ratio	*20 obs.*	*-1.98*	*-1.18*	*2.86*		*-0.21*	
DMAS737					-0.36		
t-ratio					*-0.81*		
DFLO372	1957-1994	0.31**	-0.0069*	0.023*	82.30**	0.11	**0.48**
t-ratio	*38 obs.*	*1.32*	*-4.29*	*3.14*	*1.90*	*5.06*	
DFLO372							
t-ratio							
DFLO380	1948-1994	0.12	-0.0002*	-0.0026		0.27***	**0.66#**
t-ratio	*45 obs.*	*1.07*	*-2.59*	*-0.25*		*1.19*	
DFLO380					2.52		
t-ratio					*0.024*		
DCOL357	1957-1994	-0.31	-0.0008	0.016**			**0.32#**
t-ratio	*38 obs.*	*-1.04*	*-0.32*	*1.97*			
DCOL357					42.23		
t-ratio					*0.82*		
DILL737	1974-1994	1.80*	-0.00014*	-0.11*		-2.15**	**0.68#**
t-ratio	*20 obs.*	*3.00*	*-2.68*	*-2.05*		*-1.44*	
DILL737					-0.0055		
t-ratio					*-0.15*		
DWAS372	1957-1994	0.21***	-0.0013	0.0044			**0.56#**
t-ratio	*38 obs.*	*1.21*	*-0.99*	*0.52*			
DWAS372					19.86		
t-ratio					*0.40*		
DNJE 737	1974-1994	0.80***	0.0001*	0.21*		0.95**	**0.91#**
t-ratio	*20 obs.*	*1.58*	*3.92*	*2.63*		*1.80*	
DNJE 737					-1474***		
t-ratio					*-1.72*		
DPEN367	1959-1994	-0.28	0.0002	0.015*		0.01	**0.47**
t-ratio	*35 obs.*	*-1.35*	*0.49*	*2.43*		*0.31*	
DPEN367					195.62***		
t-ratio					*1.39*		
DUTA376	1974-1994	0.47	-0.09***	0.059*			**0.54#**
t-ratio	*20 obs.*	*0.73*	*-1.20*	*2.92*			
DUTA376					-0.92		
t-ratio					*-0.15*		

* = 5%; ** = 10%; *** = 25% l.o.s.; # regressors include also one or two dummies for particular years

The results show that at 5% l.o.s. the extent of inter-cluster competition (i.e. different States competing as alternative locations for the same pool of potential industry-specific entrants) is limited. Significant negative coefficients are displayed only by 3 clusters: Computer service and data processing industry (737) in Texas and Illinois and Drugs (283) in New York. However, with a larger l.o.s. (equal to 25%), the number of significant negative coefficients are recorded also by three industries in California (Computers (357), Electronic components (367) and Aircraft (372)), two industries in Texas (Aircraft and Instruments (380)), Instruments in Massachusetts, and Computer service and data processing in New Jersey.

On the contrary, the results show a stronger influence of intra-cluster synergies (i.e. the level of other high-tech industries in the same state positively influence the development of a particular cluster). At the 5% l.o.s., 8 out of 28 intra-cluster regressors[18] show significant and positive coefficient, while only Computer service and data processing industry in Illinois display a negative coefficient which may be interpreted as a sign of Inter-industry competition on some fixed pool of generic resources (capital and/or real estates).

The empirical exercise shows also that, when interaction coefficients are taken into account, very few regressions[19] display the expected signs for both the number of incumbents (cluster size) and its squared value (squared cluster size).

6. MARKET STRUCTURE AND INDUSTRIAL SPECIALISATION IN THE GROWTH OF HIGH-TECH CLUSTERS

This section focuses on the empirical investigation of the claim that externalities - and in particular technological externalities, which are associated with knowledge spillovers - are the "engine of growth" of high-tech clusters. In particular, following Glaeser et al. (1992), we will test the empirical relevance of three alternative explanations which draw their respective theoretical background from three different streams of literature, these being economic growth, strategic management, and economic history.

The first approach stresses the role of what Glaeser et al. (1992) call "Marshall-Arrow-Romer (MAR) externality". According to this view "concentration in a city-industry helps knowledge spillovers between firms and therefore the growth of that industry and of that city" (Glaeser et al., 1992, p. 1127). This approach also predicts that "local monopoly is better for growth than local competition because it allows externalities to be internalised by innovators. When externalities are internalised, innovation and growth speed up" (ibid.)[20]. Therefore the AR story reads as follows: geographical specialisation and monopolistic power are the best conditions for knowledge externalities and, therefore, for city (or cluster) growth.

The second approach refers to the contribute of Porter (1990). According to Porter knowledge spillovers within geographically concentrated industries stimulate growth. However he also insists that "local competition as opposed to local monopoly foster the pursuits and rapid adoption of innovation" (Glaeser et al., 1992, p. 1128)[21]. The role of internal competiton is crucial in Porter's diamond of competitive advantages, in order to prevent technologically advanced industry from resting on past successes and becoming obsolete. Porter's story is the following: geographical

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[18] Which become 13 at 25% l.o.s.

[19] Five clusters: Computers in California and Massachusetts, Missiles in Texas, Aircraft in Florida, and Computer services in Illinois.

[20] This last statement, surely in line with Arrow (1962) and Romer (1986), is, in my opinion, far away from what Marshall (1921) thought about the inner dynamics of growth. For this reason, in the following section we will refer to this approach as Arrow-Romer (AR) approach. Incidentally one may also note that the AR's argument is similar to most of Krugman's ideas on this issue.

[21] "Rivalry among firms with the same home base is particularly beneficial for a variety of reasons. First, strong domestic competition create particular visible pressure on firms to improve. It also often attracts new rivals to the industry. (...) Geographical concentration of rivals in a single city or region within a nation both reflects and magnifies these benefits" (Porter, 1990, p.119-120).

specialisation and fierce competition are the best conditions for knowledge externalities and, therefore, for cities (or clusters) growth[22].

The third approach derives from two contributes of Jacobs (1969 and 1984) which underline that, in general, “the most important knowledge transfers come from outside the core industry” (Glaeser et al., 1992, p. 1128). Jacobs logically shows, and gives many historical examples, that variety and diversity of geographically proximate industries[23] together with local competition favours growth. Thus, for Jacobs, local differentiation of the industry and fierce competition are the best conditions for knowledge externalities and, therefore, for city (or cluster) growth[24].

To test these hypotheses, Glaeser et al. (1992) build a specific data-set on the 6 largest industries (2 digit SIC) in the top 170 standard metropolitan areas of USA and test a model which explains the growth rates of employment and wage (for the period 1956-1987) in a sample of 1016 city-industry, in terms of various combination of the three above mentioned main dimensions: geographical specialisation vs. geographical diffusion, industrial differentiation vs. industrial concentration, and competition vs. monopoly. We found this article very interesting and decided to test a modified version of the model which better suited the data and the specific issue of study in the paper: the development of high-tech clusters. For this reason some of the original variables have been modified in order to take into account specific definitions of specialisation, and competition within the high-tech sectors.

6.1. A MODEL

The three above mentioned theories can be formalised in a simple economic model that will be then empirically tested in order to discriminate between the conflicting explanations. Following Glaeser et al. (1992), suppose that a firm belonging to a given industry in a certain location has a production function given by $pY = A_t f\left(l_t\right)$ where p is a price index, Y is real output, A represents the overall level of technology at time t (which reflects changes in both technology and price) and l_t is the labour input at time t[25]. Each firm in the industry takes technology, prices and wages w_t as given, and maximises:

$$A_t f\left(l_t\right) - w_t l_t \tag{13}$$

the first order conditions are therefore

$$A_t f'\left(l_t\right) = w_t \tag{14}$$

which can be rewritten in terms of growth rates as

$$\log\left(\frac{A_{t+1}}{A_t}\right) = \log\left(\frac{w_{t+1}}{w_t}\right) - \log\left(\frac{f'\left(l_{t+1}\right)}{f'\left(l_t\right)}\right) \tag{15}$$

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[22] Porter thus highlights the role played by localisation externalities.

[23] “The great capitals of modern Europe did not become great cities because they were capitals. Cause and effects ran the other way. (..) Paris, Berlin and London became the genuine capitals only after they had already become the largest (and economically the most diversified) commercial and industrial city of their Kingdoms” (Jacobs, 1969, p. 143).

[24] Jacobs thus highlights the role played by urbanisation/regionalisation externalities.

[25] By choosing such functional form for the production function, which abstracts from capital inputs, “we may not capture labour-saving technological innovations and we shall not capture innovations that result only in further accumulation of physical capital” (Glaeser et al., 1992, p. 1132).

The level of technology in the region-industry is assumed to have both local and national components as follows:

$$A = A_{\text{local}} A_{\text{national}} \tag{16}$$

The growth rate will then be the sum of the growth of national technology in the industry and the growth of local technology

$$\log\left(\frac{A_{t+1}}{A_t}\right) = \log\left(\frac{\mathrm{A}_{\text{local,t+1}}}{\mathrm{A}_{\text{local,t}}}\right) + \log\left(\frac{\mathrm{A}_{\text{national,t+1}}}{\mathrm{A}_{\text{national,t}}}\right) \tag{17}$$

The growth in national technology is assumed to capture changes in the price of the product and shifts in the national technology for that industry, while the local technology is assumed to grow at a rate which is exogenous to the single firm but depends on the different technological externalities which are present in the region-industry.

$$\log\left(\frac{\mathrm{A}_{\text{local,t+1}}}{\mathrm{A}_{\text{local,t}}}\right) = g(\text{specializ., local monopoly, diversif., initial conditions}) + e_{t+1} \tag{18}$$

If we set $f(l) = l^{1-\alpha}$, where $0 < \alpha < 1$, and we combine (6.15), (6.17), and (6.18) we obtain:

$$\log\left(\frac{l_{t+1}}{l_t}\right) = -\log\left(\frac{w_{t+1}}{w_t}\right) + \log\left(\frac{\mathrm{A}_{\text{national,t+1}}}{\mathrm{A}_{\text{national,t}}}\right) + g\ (s, lm, d, ic) + e_{t+1} \tag{19}$$

where *s* stands for specialisation; *lm* for local monopoly; *d* for diversification, and *ic* for initial conditions and *e* is a white noise error term, assumed well behaved.

Growth in nationwide industry employment is assumed to capture changes in nationwide technology and prices; workers are assumed to participate in a nationwide labour market[26] so that wage growth will be a constant across state-industries. Equation (19) then allows one to associate the growth of employment in a state industry (or cluster *q*) with measures of the technological externalities proposed by the different theories as follows:

$$\begin{aligned} LGMSI_q &= aLGMUI + bLWIN75_q + cLMIN75_q + dSPEIN_q + \\ &+ eCOMINHT_q + fDIVINHT_q + e_q \end{aligned} \tag{20}$$

where $SPEIN = SPEINHT$ in model 1 and $SPEIN = SPEINTOT$ in model 2, 5 and 6 (see table 9).

The variables of the estimated version of model has been based on the following variables.

Dependent variable:

$LGMSI_q$ = Log (Employment in 1995/ employment in 1975) in the state-industry.

Independent variables:

LGMUI = Log (US employment in 1995/US employment in 1975) in the industry.

$LWIN75_q$ = Log of wage in the state-industry in 1975 in thousand dollars per years (calculated as the ratio between the annual payroll and the employment in the state -industry).

$MIN75_q$ = Log of employment in the state-industry in 1975.

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26 This assumption is crucially dependent on the US institutional framework. The empirical estimates will thus be produced on US data.

$SPEINHT_q$ = index of state-industry relative geographical specialisation within the HT macrosector in 1975 (calculated as a modified employment location quotient were the industrial total is calculated only on the high-tech part)[27].

$SPEINTOT_q$ = alternative index of state-industry geographical specialisation in 1975 (calculated as a generic location quotient based on employment).

$COMINHT_q$ = index of relative local intrasectoral competition in 1975 (calculated as the ratio of the number of firms per workers in industry *i* in state *s* and the number of workers in the same industry in the US)[28].

$DIVINHT_q$ = index of relative diversification of the state within the high-tech macrosector in 1975 (calculated as a modified Herfindhal index where the shares are calculated on the remaining high-tech sectors). Because of its formulation $DIVINHT_q$ is an inverse index of diversification. The lower is the value of the index, the higher is the level of diversification of the state within the group we classified as high-tech industries.

6.2. THE DATA

The data used in this exercise is the original time series dataset we built from County Business Patterns data in order to test the macro-ecologic approach. Since we were able to collect historical data (at this fine level of spatial and sectoral level of disaggregation) only for the US, we did not have to worry about international comparisons but only about the changes in the US industrial classification definition, SIC (the most recent occurring in 1988).

The final dataset is composed of 112 observations on the growth rate of different variables between 1975 and 1995 for 7 sectors within 16 US States[29]. The sectors involved in the analysis are (in the original US SIC codes and definitions): 283, Drugs; 356, Office and computing machines; 367, Electronic components and accessories; 372, Aircraft and parts[30], 737 Computer and data processing services, 7391 Research and development laboratories[31].

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[27] SPEINHT = (employment in industry *i* in state *s* / total high-tech employment in state *s*) / (US employment in industry *i* / total high-tech employment).

[28] COMINT = (firms in industry *i* in state *s*/employment in industry *i* in state *s*) / (firms in industry *i* in the US / employment in industry *i* in the US).

[29] These 16 states have been selected as the most technologically advanced in the US (i.e. the one with the largest number of employees or establishment in the high-tech sectors) either in 1956 or in 1994. The complete list is as follows: Arizona, California, Colorado, Connecticut, Florida, Illinois, Kansas, Massachusetts, Michigan, New Jersey, New York, Ohio, Pennsylvania, Texas, Utah, Washington. From a geographical perspective they offer a non-biased sample of both the 9 Census divisions and of the 4 Census regions. For withheld employment data we used the class size average, for each payroll missing data we constructed an "artificial" payroll data by using the employment figures obtained as above and a wage proxy calculated on "similar" sectors. (i.e. when employment and payroll data for Colorado in 1975 were missing for industry 372 Aircrafts and parts, we used the average of the employment size class and an artificial payroll figure calculated as the product of the "average" employment and the wage of sector 3724 Aircrafts engine and engine parts).

[30] Sector 376, Guided missiles, space vehicles, and parts, had to be dropped because most of the figures on employment were withheld for privacy reasons.

[31] This sectors became 8371 Commercial physics research, after the changes in SIC occurred in 1988. We are grateful to Y.D. Funderburk (US Census Bureau) for helping us in matching precisely the sectors through the different SIC codes and for supplying some additional 1975 data that we did not collect in our original data-set.

Table 8. shows the four fastest and slowest growing state-high-tech industries in the period 1975-95.

Table 8. Fastest and slowest growing state-industries (employment) in the period 1975-1995

States	*Industries*	*lgwsi*	*speinht*	*speintot*	*cominht*	*divinht*
COLORADO	Computer services	2.714	1.022	1.282	1.399	0.360
UTAH	Instruments	2.702	0.399	0.307	4.496	0.277
UTAH	Computer services	2.598	1.710	1.316	1.167	0.292
MASSACHUSETTS	Computer services	2.585	0.575	0.881	1.878	0.294
average fastest growing industries		**2.650**	**0.927**	**0.946**	**2.235**	**0.306**
KANSAS	Computer and o.m.	-1.285	0.352	0.790	0.692	0.725
NEW JERSEY	Computer and o.m.	-1.290	0.633	0.822	1.873	0.262
NEW YORK	Aircrafts	-1.560	0.550	0.779	0.910	0.290
OHIO	Computer and o.m.	-1.595	0.891	0.693	0.701	0.305
average slowest growing industries		**-1.433**	**0.607**	**0.771**	**1.044**	**0.395**
differences		***4.082***	***0.320***	***0.176***	***1.191***	***-0.090***

Table 8. gives three impressions. First, rapidly growing state-industries were more geographically concentrated (both in relative[32] and in absolute terms) than rapidly declining ones. Second fast growing state-industries were more competitive than shirking state-industries. Third, the effects of diversification on the growth performance of state-industries is positive (i.e. more diversified clusters grow more than the others) but weak[33].

The table seems therefore to support the interpretation on the genesis of externalities, proposed by Porter, which states that the engines of growth are geographical specialisation and local competition. However, a detailed econometric analysis is needed in order to test, in greater detail, the above mentioned hypotheses.

6.6.3. THE RESULTS

Table 9 shows the results for different empirical specifications of the model. R^2 coefficients of every model are quite high for a cross-section analysis (they vary between 0.65 and 0.69) and stable. The best fit of the regression is achieved by model 6 (which, as will be discussed below, test as the same time both the AR's and the Porter's theories).

All regression equations have been tested for serial correlation (Lagrange multiplier test), functional form mispecification (Ramsey RESET test), non normality of residuals (skewness and kurtosis of

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32 With respect to the high-tech industry as a whole.

33 The table also shows the westward shift of high-tech industries (fastest growing state-industries are in the Mountains Census Division) and the different stages of development of industrial high-tech industries (with computer services rapidly growing and computer manufacturing declining). This last result can be seen also as a prove of the tertiarisation of advanced economies.

residuals), heteroskedasticity (Breusch and Pagan test), and multicollinearity (correlation ratios between dependent variables and auxiliary regressions) and no significant deviation from the classical model could be detected, apart from heteroskedasticity which has been corrected by using White's procedure.

Table 9. The engines of high-tech clusters' growth

models	1*	2*	3*	4*	5*	6*	7*
constant	4.34	4.69	2.82	4.71	3.34	2.9	3.19
t-ratio	*4.86*	*5.25*	*2.48*	*5.54*	*3.18*	*2.61*	*2.99*
LGMUI	0.99	0.99	1.05	0.98	1.08	1.08	1.05
t-ratio	*13.16*	*13.51*	*12.94*	*13.3*	*13.75*	*13.55*	*13.08*
LWIN75	-0.84	-0.89	-0.67	-0.85	-0.71	-0.69	-0.68
t-ratio	*-2.35*	*-2.5*	*-1.86*	*-2.5*	*-2.12*	*-1.95*	*-1.98*
LMIN75	-0.25	-0.29	0.16	0.27	-0.22	-0.19	-0.18
t-ratio	*-5.56*	*-6.45*	*-3*	*-6.33*	*-4.07*	*-3.62*	*-3.44*
SPEINHT	0.01						
t-ratio	*-0.07*						
SPEINTOT		0.09			0.15	0.14	
t-ratio		*2.78*			*3.79*	*3.63*	
COMINHT			0.18		0.22	0.22	0.17
t-ratio			*2.07*		*2.53*	*2.55*	*2.02*
DIVINHT				-0.53	-0.58		-0.48
t-ratio				*1.12*	*-1.28*		*-1.07*
Adj. R sq.	0.65	0.66	0.67	0.65	0.69	0.68	0.67
n. of obs.	112	112	112	112	112	112	112

* indicates that the regression parameters have been estimated using White's corrected version of the variance-covariance matrix of parameters. Al regression coefficients are signigifacant at 5% l.o.s. (a part from LGWIN75 in model 6 and DIVINHT in all models which are both significant only at 20% l.o.s.)

The different specifications allow one to identify both the single and the combined effects of the different kinds of externalities on the growth of high-tech clusters. All specifications include a set of control variables such as: national employment growth (*LGMUI*) which corrects for demand shifts, log of wage in the state-industry in 1975 (*LGWIN75*) which corrects for generic movement of firms towards low-wage areas, and log of employment in the state-industry in 1975 (*LGMIN75*) which corrects for generic movement of workers toward high-employment state-industry. Alternatively and somehow more sensibly, one can interpret the negative coefficients on the initial values of employment and wages as an indirect way to measure the geographical westbound shifts of high-tech industries in the US from the old industrial East coast towards the Mountains and the Pacific (where these sectors were still in the first development phases and where wages were lower). All control variables have the expected signs. High initial employment and high wages in a cluster lead to slower growth (negative coefficients for both *LWIN75* and *LMIN75*); while employment growth in the cluster is positively correlated with US wide industry growth.

Table 9 presents six different empirical specifications of the same basic model. The first three specifications look at each externality effect in isolation while the remaining ones test the empirical relevance of the three theories through a couple of coefficients.

The first specification uses *SPEINHT* as the index of geographic specialisation, and the parameter is not significantly different from zero. In the second specification we use the alternative index for geographic specialisation *SPEINTOT* (where the state-industry is compared with the total of manufacturing and service activities) and we find the coefficient to be positive and significant. Thus, sectoral specialisation in specific high-tech industries fosters growth. This result is consistent with both AR and Porter and in contrast with Jacobs.

The third specification analyses *COMINHT*, which is an index of competition (or, alternatively, an inverse index of monopoly power). The parameter is positive and significant suggesting a positive correlation between the extent of local competition and the growth of the cluster[34]. This result is thus consistent with Porter and Jacobs but in contrast with AR.

The fourth specification, by introducing *DIVINHT*, studies the effect of industrial diversification. Although the parameter had the correct negative sign (meaning that a lower value of the Herfindhal index, which means a higher diversification in the other h-t sectors, is positively correlated with the cluster growth rate), it shows a lower significance[35]. Thus we have no strong empirical support for an important part of the Jacob's theory which, for high-tech industries, will take count of the inter-industry (i.e. within the whole high-tech sector), technological externalities and knowlege spillovers[36].

The fifth specification tests the significance of all parameters together (*SPEINTOT*, *COMINHT*, and *DIVINHT*). The empirical evidence thus supports the theory put forward by Porter, and here adapted to the case of high-tech industries, which considers intra-industry technological spillovers and intra-industry local competition and rivalry as the spurs to innovation, growth and success of clusters.

The last two specifications test the three theories in a more formal way (each time with only two relevant parameters). The estimated coefficients of model 5 give stronger support to Porter's theory since both values of *SPEINTOT* and *COMINHT* are positive and significant; and are definitely against AR. Model 6 is partially supporting Jacobs in the sense that while the coefficient of *COMINHT* is positive and significant, the coefficient of *DIVINHT* has the expected (negative) sign but its statistical significance is low.

7. WHY DO HIGH-TECH FIRMS CLUSTER? SOME EMPIRICAL CONSIDERATIONS

If one jointly considers the empirical results of section 3 and 6, then a descriptive conclusion would merely state that, while the actual degree of innovative industrial specialisation of an area (see section 3) is heavily dependent on the presence of large establishments (which enjoy higher economies of scale), the growth rate of its high-tech employment (see section 6) is fostered by the presence of a competitive environment where small firms are predominant.

A tentative explanation of the different relations existing between the average firm's size (in a given industry and region), the degree of specialisation of a region, and the growth rate of its industry employment reads as follows. The relative specialisation of a given area (as measured by the industry location quotient) is explained in terms of a larger average size of firms. Large high-tech firms are more efficient (because of the existence of economies of scale in some part of the production process, say in R&D activities) and they acquire growing market shares. The region becomes nation-wide acknowledged as the centre of the industry, and the regional level of industry employment increases at the expenses of other industries (causing sectoral changes in the regional industrial structure of production) and/or of other regions (causing regional changes in the national geographic structure of production, and the inflow of skilled high-tech industry workers). The negative effects of scale economies on employment are in fact more than compensated for by the increasing market share. The process continues up to the point where regional firms as a whole have reached a

34 This is consistent with lots of anecdotal literature on the business climate of successful high-tech clusters such as Silicon Valley, Research Triangle etc.

35 It is always significant only at the 20% l.o.s.

36 The existence and the relevance of these spillovers has been shown by Scherer (1982) presenting systematic evidence that around 70% of innovation in a given industry are used outside that industry.

dominant position in the market and the growth of any single firm is obtained at the expenses of the remaining firms in the region. From this point onward any increase in the average firm size necessarily implies a process of regional concentration and therefore, because of economies of scale, the reduction of the employment growth rate[37].

An alternative explanation, which directly relates to the organisation ecology literature (Hannan-Freeman, 1989) and that we have adapted to the development of industrial clusters is the following. In the early stages of development of a cluster small and pioneers firms enter from outside the region and/or are generated by a spin-off process from existing firms (which may well be doing business in other industrial sectors). Thus the positive relation between growth and small firms size in the early "heroic" stages of development of an industrial cluster is explained. However, when the industry begins to be important in the region's economy and the first signal of input competition and congestion begins to appear, then these small and creative firms stop being the fittest organisational form. They are gradually substituted by larger and more structured firms which, by enjoying scale economies in a technology that is gradually becoming "stable", make full use of their superior organisational and market power to make profits and grow. The locational pattern of established high-tech industries is therefore determined by economies of scale much more than by agglomeration economies.

Finally it is worth to stress that the empirical analyses performed in this paper have add new contributions to the existing knowledge of the structure and dynamics of innovative industrial clusters in many respects. In particular:

i) The analyses performed in section 2 confirmed the positive influence of the existence of a local pool of skilled labour force (Marshall, 1920; Krugman, 1991a), the strength of the technological infrastructure (Feldman 1995), the degree of trade openness of the cluster (Porter, 1996), and a negative influence of corporate income tax rate and unemployment rate (Storper-Walker, 1989; Hirshleifer, 1993).

ii) The analyses of section 3, to my knowledge, are the first empirical studies devoted to measure the relative importance of scale versus agglomeration economies for high-tech sectors and they are based on an extremely wide database. Furthermore in the same section an analysis of inter-industry and inter-cluster spillovers has been performed together with an empirical test of the relevance of locational shadowing (Arthur, 1990).

iii) In the analyses of section 5, which bear some similarities to those performed by Swann (1998) and Swann - Prevezer (1996), we attempted to give empirical consistency to the ecological approach (Dendrinos - Mullally 1985; Hannan - Freeman, 1989; Nijkamp - Reggiani, 1998) to spatial economics and location theory.

iv) In the analyses of section 6 we applied the original empirical framework proposed by Glaser et al. (1992) to the growth of US high-tech cluster, obtaining some original and interesting results which support Porter's (1990 and 1996) explanation.

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[37] Eventually, as the process continues, the regional industry employment growth rate decreases until it become negative and the industry employment level in the region is reduced.

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