45th Congress of the European Regional Science Association
23-27 August 2005 Vrije Universiteit Amsterdam

Technological change and industry competitiveness through the evolution of localised comparative advantages - The case of Italy

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Abstract

The influence of technological change on industry performances is nowadays being increasingly investigated under the broad category of "national systemic competitiveness". Moreover theoretical works have shown that the relationship between technology and economic performance not only takes different forms in different socio-economic contexts, but is also powerfully influenced by the way that innovation processes evolve over time along strongly localised patterns.

The present study is focused on the evolution of trade competitiveness of the manufacturing sector in Italy over the past ten years and addresses the role played by technology based comparative advantages at the local level in shaping the model of national competitiveness. The data used in the analysis, drawn by the *Enea Observatory* on high-tech industries, are based on trade statistics at the SITC five digit level and are spatially referenced to the Italy NUT3 regional partition. The effects of localised trade specialisation on manufacturing trade competitiveness have been assessed through spatial econometric techniques for local modelling. Results from econometric estimates support the existence of a significant relationship between the evolution of Italy's manufacturing trade competitiveness and trade performance in high-tech industries according to a dynamic trend deeply rooted at the local level.

Keywords: trade competitiveness, technological change, localised comparative advantages
JEL: F1 Trade O3 Technological change R15 Econometric Models

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1. Introduction

There is a widespread agreement today on the role played by technological change and increasing returns to knowledge in shaping competitive advantages of nations. However, important differences between national economic systems have been recognised and, in recent years, the need for a more comprehensive and systemic analysis of national competitiveness has grown rapidly (Hämäläinen, 2003; Palma, 2002; Fagerberg, Guerrieri and Verspagen, 1999).

A renewed interest has emerged in order to explain the way in which knowledge externalities are generated, to the extent that they may be crucial for increasing returns. Easier access to relevant knowledge through such externalities, is in fact at the origin of faster rates of technological change and innovation to firms which benefit from knowledge flows. If knowledge flows only take place within well defined spatial boundaries (regional or national), then some regions or countries, given an initial technological endowment, will deepen their patterns of specialisation through cumulative processes. Thus the geographical dimension of knowledge spillovers plays a specific role in shaping national and regional patterns of specialisation and comparative advantages (Sjöholm, 1996; Grossman and Helpman, 1991; Krugman, 1991).

From a more theoretical perspective, other authors have investigated the properties of knowledge that can explain the localised nature of knowledge spillovers. Most contributions highlight the fundamental role of *geographical proximity* in facilitating the transmission and absorption of technological and scientific knowledge. Knowledge diffuses mainly through informal means, like interpersonal contacts, face-to-face communications, meetings, seminars, on-the-job training and other similar mechanisms, whose effectiveness decreases with the distance between agents (Feldman, 1994). In addition, the more tacit and complex the knowledge base, especially when it is part of larger systems, the more likely it is that geographical proximity will play a relevant role in facilitating the transmission of knowledge (Breschi and Lissoni, 2001; Audretsch and Feldman, 1996; Breschi and Malerba, 1996; Winter 1987). In this particular respect, one can then argue that the relationship between technology and economic performance not only takes different forms in different socio-economic contexts, but is also powerfully influenced by the way that innovation processes evolve over time along strongly localised patterns (Breschi and Palma, 1999).

In this paper we focus on the evolution of trade competitiveness of the manufacturing sector in Italy over the past ten years and address the role played by localised comparative advantages in shaping comparative advantages at the national level. Moving from recent developments of international trade competitiveness, which point out the growing relevance of comparative advantages in high-tech industries (Ferrari et al., 2004), we aim to provide an empirical evaluation of the extent to which, in Italy, trade competitiveness in manufacturing has been affected by localised patterns of comparative advantages in high-tech industries. In order to assess the localised character of this relationship, we have adopted a spatial econometric approach based on geographically weighted regression in which spatial-non stationarity is explicitly taken into account (Fotheringam, Brunsdon and Charlton, 2002). The data used in the analysis, drawn by the *Enea Observatory* on high-tech industries, are based on trade statistics at the SITC five digit level and are spatially referenced to the regional partition of Italy at the NUTS3 level, that corresponds to the 103 counties.

The paper is organised as follows. In Section 2, after a brief illustration of major trends which have recently characterised manufacturing trade competitiveness in Italy, we give some preliminary evidence on the dynamics of the spatial patterns of trade in both manufacturing and high-tech industries. The spatial structure of data is further explored in Section 3, where several spatial econometric issues are examined and the use of geographically weighted regression is discussed. The main results from econometric estimates are presented in Section 4, while concluding remarks are reported in Section 5.

2. Recent developments of Italy's trade competitiveness: major trends in national performances and drifts in regional patterns

2.1 Recent trends in Italy's trade competitiveness

The strong expansion of world trade over the past twenty five years has been boosted by rapid growth in the manufacturing sector with increasing shares of high-tech products. Among industrialised countries, Japan and the US gained prominent position, while European countries made up for part of the cumulated delay only in the early '90's. During the last decade, however, several countries in the EU area turned out to increase their competitiveness in high-tech manufacturing in terms of both market shares and trade balances, with various contributions from major European countries (France, Germany and United Kingdom) and a number of smaller countries in the North European area (Ireland, Sweden, Finland and, recently, Denmark). The competitiveness of these countries has been in fact the outcome of

growing specialisation in specific high-tech sectors along the lines of major technological trends, with sharp differences in the trade patterns of individual countries.
Unlike the EU trend of recovery in technological competition, Italy showed a distinctly poor trade performance in the high-tech sectors while deepening its previous weakness in this area. Since the second half of the ‘80s, Italy’s loss of technological competitiveness emerged trough a steep decrease of export shares and a trade deficit whose deterioration has been noticeable over the past decade. In contrast with the successful performance in the medium-low tech sectors of traditional specialisation and the outstanding results due to the extraordinary exchange devaluation in 1992, Italy’s deteriorating competitiveness in the high-tech sectors has been uninterrupted giving rise to a wide gap with the overall EU performance. Moreover, with respect to EU countries, trade deficits in the high-tech sectors has proved to be even larger than that recorded in extra-EU markets (Ferrari et.al, 2004).
After 1996, however, a new process of Italy’s deterioration in competitiveness started with steady erosion of export shares in the medium-low tech sectors which affected the performance of the manufacturing sector as a whole. Quite interestingly, this new loss of competitiveness increased irrespective of any changes in the economic framework. Despite the recovery of world demand in 2002, Italy’s manufacturing export flows have been in fact decreasing with further remarkable accentuation in the high-tech sectors. Moreover, the decrease of export flows has been even larger than the decrease of import flows due to stagnation in domestic demand. The trade deficit in the overall manufacturing sector thus increased and, for the first time, even stagnation in domestic demand was not sufficient to compensate the negative balance (Ferrari et.al, 2004).

2.2 Regional trade patterns in manufacturing and high-tech sectors

The development of industrial activities in Italy has been traditionally characterised by the presence of small and medium-sized enterprises with uneven spatial distribution and peak concentration in Northern regions. More specifically, the birth and evolution of locally rooted networks of firms allowed the emergence of a "core" pool of competencies at the national level which, during the ‘80s, turned out to establish themselves as the so-called Italy’s *business district-model* (Becattini, 1990).
Until the early ’90’s the business district-model played a prominent role in shaping Italy’s competitiveness and even more recently most district areas showed remarkable trade performances compared to other territories (Bronzini, 2000). However, the overall

contribution of district areas to Italy’s manufacturing export became less as the positive effects of the exchange devaluation gradually disappeared. Today a more diffused crisis does not even allow significant discrimination between district and non-district areas (Palma, Coletta and Zini, 2004).

In the present paper we carry out a more in-depth analysis of spatial distribution of trade in order to highlight the role played by comparative advantages at the local level in shaping the manufacturing spatial pattern of trade and hence competitiveness at the national level. We investigate in particular the spatial relevance of comparative advantages in high-tech sectors as a whole, to the extent that weak trade performance in these sectors has proved to be a key component in the process of Italy’s deterioration in competitiveness. As mentioned above, the concept of geographic proximity plays in fact a more significant role the more tacit and complex the knowledge base is, thus emphasizing the localised character of comparative advantages in high-tech industries. Moreover, due to the specific character of technology and the need for a detailed account of its relevance, the whole of the high-tech industries is here referred to according to the original methodology introduced by the *ENEA Observatory on Italy’s technological competition* [1].

This methodology relies primarily on a more accurate definition of high-tech sectors in contrast with the most widely adopted approach in the literature based upon the use of some indicators of technological intensity, such as the ratio of R&D expenditure on sales. The reliability of indicators based on R&D intensity has been in fact questioned on various grounds: first, there is the issue of the technological heterogeneity of products within a given sector; second, R&D expenditure accounts for only one of the channels for innovation within a given firm; third, R&D expenditure is generally available only for the principal product group of a given firm (Patel and Pavitt, 1995). In order to achieve a more satisfactory definition of high technology sectors, specific inquiries have been conducted in manufacturing firms as well as in public and private research centres. The selection of high-tech sectors was based on the SITC Rev. 3 nomenclature of foreign trade at the five-digit level. For each sector, experts in technology were then asked to evaluate products on the basis of a number of parameters including R&D intensity, the degree of automation in production, characteristics of product use, and the product life cycle. In other words, the approach used

[1] Cespri-Bocconi, Milan Polytechnic and University of Rome “La Sapienza” are official partners with Enea in the Observatoty.

here identifies high technology sectors according to a *bottom-up* procedure, in contrast with the *top-down* procedure that has been traditionally applied (Amendola and Perrucci, 1993)[2].
In order to highlight the higher spatial concentration of high-tech trade flows, we offer some preliminary evidence on a set of indicators that measure the extent to which trade is geographically clustered:

- *C1 concentration ratio*; i.e. the share of exports held by the largest county in terms of exports;
- *C4 concentration ratio*; i.e. the share of exports held by the four largest counties in terms of exports;
- *Herfindahl equivalent number* (HEN): i.e. the inverse of the Herfindahl index, given by the sum of the squared shares of exports of all 103 counties.

The analysis of the data at this stage shows some remarkable features of the spatial distribution of trade in the high-tech sectors from both a structural and a dynamic point of view:

1) Trade in the high-tech sector is far more spatially concentrated compared to the manufacturing sector as a whole. The C4 concentration ratio of exports for all manufacturing sectors is mostly around 30%, whereas the same ratio for the high-tech sectors is between 60% and 45% (Table 1). This result is confirmed by the Herfindahl index, which shows a degree of spatial concentration in the high-tech sectors over three times higher than that of the manufacturing sector as a whole.

2) From a dynamic perspective a clear trend of spatial diffusion characterises the evolution over time of the spatial concentration of high-tech exports. This process appears to be even more significant than in the manufacturing sector with sharp accentuation in the late '90s.

Actually, the analysis carried out in these terms does not provide much information about the way that export flows are spatially structured. A given value of spatial concentration can indeed correspond to different spatial configuration of the data. Therefore it is important to look at the spatial distribution of export flows across Italian regions which points out major changes occurred over the past decade.

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[2] The Enea approach and high-tech classification have been recently adopted by the Oecd with no substantial changes (Hatzichronoglou, 1997).

While the most representative manufacturing export share held in the Northern regions proved to be rather stable (75%), the spatial configuration of exports has continuously adjusted from the West to the East with further diffusion processes within regions[3] in the East. To a certain degree, a diffusion process of manufacturing exports flows also occurred toward Central regions while in Southern regions only slight variations in the spatial export distribution could be observed around the exchange devaluation period (Table 2). This process appeared to be even more significant in the high-tech sector bringing into evidence a dramatic decrease of the export share held by the regions in the North-West (41% in 2002 against 49% in 1991).

The overall diffusion of manufacturing export shares across the Italian regions has been therefore characterised by both significant loss of the North-West areas and uneven distribution in the rest of the country, with sharp accentuation in the high-tech core. However, it is still not clear at this stage of the analysis to what extent the local character of comparative advantages in high-tech industries can be thought of as an explanatory factor of the time varying spatial pattern arising in manufacturing. The analysis of export shares is in fact carried out simply with regard to regional units, whereas no element is introduced about the dimension of the data in the geographical space. This means, in other words, that the only availability of the attribute variable is not sufficient to gain insights into the spatial process underlying the phenomenon investigated. Instead explicit consideration of the geo referenced character of the data should be taken into account for proper spatial modelling. This view is fully adopted in the following sections where special attention is devoted to the role of localised spatial variability in shaping data variability across the whole geographical space under study.

3. Modelling local comparative advantages

3.1 Local models for spatial data

In recent years a renewed interest has been growing among geographers about the specific relevance of methods for spatial data analysis. Along the lines of the wide existing literature on “local” approaches to the study of data variability (Hardle, 1991; Barnett et al., 1990), the issue of spatial variation in the geographical space has been brought to the fore in socio-economic modelling.

[3] In the present paper regional division stands for Italy’s NUT 1 level (North-West, North-East, Centre, South

Unlike physical processes, social processes are usually not constant over space bearing a certain amount of spatial non-stationarity. The assessment of data variability across space has to reflect the association between each data measurement and the location at which the measurement is taken, and if the data generating process is supposed to be non-stationary over space, global statistics which summarise major characteristics of a given spatial data configuration might be very misleading locally. In these terms even those measures of spatial dependency, such as the Geary and Morans'I coefficients, whose aim is to detect the tendency of spatial data to cluster in space, yield approximate indications from a local perspective averaging out different degrees of spatial variation around different locations. The same applies equally to model fitting if local spatial variation is suspected to exist in the relationship under study. Model parameters relate in fact to the study area as a whole and might lead to poor understanding of the relationship investigated if this exhibits significant local spatial variation. In this regard further evidence has been also provided on the relatively small impact of the addition of spatial autoregressive term to models in order to account for spatial non-stationarity.

Suitable methods to deal with spatial non-stationarity have been recently proposed by Fotheringam, Brudson and Charlton who developed an alternative regression technique termed Geographically Weighted Regression (GWR) for the local analysis of relationships in multivariate data sets. Addressing the general regression model:

$$Y_i = \alpha_0 + \sum^{J}_{j=1} \alpha_{ij} X_{ij} + \varepsilon_i \qquad (1)$$

regression parameter estimates are allowed to vary according to location in space, meaning that each coefficient in the model is now a function of i, a point within the geographical space of the study area. Parameter estimation is in fact based on weighted minimisation of the sum of the squared residuals yielding the following formula:

$$\hat{\alpha}_i = (X_t w_i X)^{-1X^t} w_i Y \qquad (2)$$

where X_t denotes the transpose of matrix X and w_i is a matrix with diagonal elements w_{i1} w_{i2} ….. w_{in} and off diagonal elements all zero. The matrix α_i varies with i and so produces a

and Islands) while the term region stands for the NUT 2 level.

unique set of parameter estimates for each point i. This result can be compared to that obtained in kernel regression, the difference being that in kernel regression the weighting is in the attribute space whereas is in GWR the weighting is in the geographical space.

Similarly to kernel density estimation (Silverman, 1986) the weighting scheme for w_i is expressed as a function of distances between points:

$$w_{ih} = exp\ (-k^{-1} d^2_{ih}) \qquad (3)$$

where d_{ih} is the distance between two points i an h. Under this form the weight is a decreasing function of the distance from i and it is such that for data distant from i the influence is quite negligible. The role of the parameter k, the analogous of the bandwith in kernel density estimation, appears then to be crucial in the calibration of the spatial weighting function. The choice of the kernel bandwith is usually determined by either cross-validation (Cleveland, 1979 for local regression and Bowman, 1984 for kernel density estimation) or Akaike minimisation (Hurvich et al., 1998). However, the latter has the advantage of being more general in application and can be also used to assess whether GWR provides a better fit than a global model, taking into account the different degrees of freedom in the two models.
Finally, a test based on Monte Carlo approach has been developed in order to assess the statistical significance of spatial variation for a given set of local parameter estimates. The Monte Carlo test is based on the sampling distribution of the standard deviation of the GWR parameter estimate under the null hypothesis that the global model holds, and works well in most GWR applications.

3.2 Model framework

As mentioned above, the aim of the present paper is to evaluate empirically to which extent Italy’s trade competitiveness in manufacturing over the past decade has been determined by the evolution of localised comparative advantages in high-tech industries. To this end, we have estimated a regression model where the dependent variable is the ratio of manufacturing exports to the number of industrial workers attributed to any given county. As far as explanatory variables are concerned, we used the ratio of high-tech exports to the number of industrial workers attributed to any given county as a measure of localised comparative advantages in the advanced industries[4].

In order to take into account the effect of scale economies on export propensity, we also introduced a variable measuring the average number of workers at the firm level for any given county[5]. The relevance of this variable in the relationship investigated is moreover concerned with the prominence of small medium size enterprises in shaping the Italian model of competitiveness. Actually, to capture the effect of a *made–in-Italy* specific factor on manufacturing trade performance we constructed an additional spatial variable based on the export propensity in the district areas (Ice, 2000). We acknowledge however that the zone system based on the district areas is incompatible with that based on the county partition giving rise to major estimate problems when spatial variability is to be assessed (Fotheringham, Curtis and Densham, 1995; Openshaw and Taylor, 1979). The cross border character of the district areas with respect to the county partition then suggested to us to construct a first order spatially lagged variable of the district based export propensity[6]. For each county, the spatially lagged explanatory variable is calculated as the weighted sum of district based export propensity of neighbouring counties, where the matrix of weights (*W*) used is specified in terms of simple contiguity with rows standardised to unity.

For all the years considered [7], the model to be estimated is formally expressed as follows:

$$LCAM_{it} = \alpha 0 + a1LCAHT_{it} + \alpha 2BD_{it} + \alpha 3WDISTR_{it} + \varepsilon_{it} \qquad (4)$$

where [8]

i = 1 ….. 103 (counties)

$LCAM_{it}$ = ratio of manufacturing exports to the number of industrial workers of county i in year t

BD_{it} = business dimension based on the average number of workers at the firm level of county i in year t

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[4] The two ratios have been built on the same aggregate variable in order to take into account the whole degree of industrialisation in each county. The source for the number of the industrial workers at the county level is the national census of industry, 1996.

[5] The variable introduced is still designed to play a structural role and for all the years studied we used data from the 1996 national census of industry.

[6] For counties without districts we used data on medium-low tech export flows in order to account for an export propensity consistent with that of the district areas.

[7] The sequence of the years 1991, 1993, 1995, 1996, 1998, 2000, 2002 has been selected for evaluating the various stages of Italy's trade competitiveness during the '90s. More specifically the years 1991 and 1993 have been chosen in order to evaluate the period around the lira devaluation; the years up to 1998 have been considered in order to evaluate the whole course of the exchange effects on competitiveness, while the last two years 2000 and 2002 are representative of the end of this course as well as of international economic recovery.

$LCAHT_{it}$ = ratio of high-tech exports to the number of industrial workers of county i in year t
W = spatial weights matrix (103 x 103, with rows standardised to unity)
$WDISTR_{it}$ = weighted sum of district based export propensity of first order neighbouring counties in year t
Two versions of the model have been proposed with respect to the underlying geographical system. Different specifications of the geographical space are in fact expected to give rise to different results in term of significance of local estimates, providing further insights into the "localised" relationship investigated. In our experiment we have assumed a basic coordinate system represented through map distances between chief towns of each county. The second geographical system is based instead on the shortest distances between chief towns of each county, allowing for additional information on the cohesion between territories for which the existence of well structured communication networks plays a prominent role. Despite its apparent simple specification, the proposed model is in fact tailored to enhance local variability through suitable specifications of the geographical space in the estimation procedure (Palma and Zini, 2005).

4 Estimation and empirical results

4.1 Empirical evidence

According to the GWR estimation approach, significant differences should be highlighted in local parameter estimates with respect to global parameter estimates if a relationship between variables is distinctively represented at the local level. Regression results are therefore provided for both global and local estimation and compared for all the years investigated[9] and are shown in tables 3-6.

All global regressions yield a good fit of the data with slight increase of the R-squares in the second part of the decade[10]. All three regression parameter estimates have moreover the

[8] LCA stands for local comparative advantage.
[9] Regression estimates are based on standardised variables for proper time comparisons and on the use of an adaptive kernel in order to account for complex spatial non-stationarity of the variables observed.
[10] The presence of *influential* observations (i.e. individual data values that have a disproportionate influence on the fit of the model) has been also considered before testing the regression models. In our case all the variables for the two counties of Turin and Milan have replaced with the first order spatially lagged variables. See more on *influential* observations in Haining, (1990) who proposes 'perturbing' or 'smoothing' values that are suspected to be influential, rather than deleting them.

expected positive sign and are highly significant, although <major differences can be noticed in the values of the single parameter estimates through time.

For the high-tech parameter a rather stable dynamics is recorded with the only exception of the two peaks in 1993 and 2000, in which there is clear evidence of the effect of the exchange devaluation episodes occurred for the lira and the euro respectively. Increasing values of the “business dimension” parameter estimate are instead recorded up to 1996 with only a moderate decrease in the second part of the decade (1998-2000-2002), giving some support to the idea that trade performance in Italy shows progressive higher sensitivity to this factor. Finally, for the district-based export propensity parameter a steep rise is observed up to 1998, while a sharp downturn follows in 2000, in 2002 reaching values even smaller than those recorded in 1991.

Spatial variation in the relationship under study is further highlighted by the GWR estimates. The model fit shows in fact a significant improvement, in particular with respect to the AIC whose decrease can be evaluated independently of the difference in the degrees of freedom. Moreover no appreciable differences can be noticed between the model fit based on map distances and that obtained from the shortest distances, although the AIC criterion gives smaller values in the latter[11].

The analysis of the GWR regression parameter estimates gives interesting insights into local variation of the high-tech parameter for which statistical significance is found over nearly all the decade. More specifically, a wide gap is detected for the high-tech parameters between the Northern counties and the rest of the country, while a clear-cut descending trend of the parameter values emerges between 1991 and 1998, with the only exception of 1993 when the extraordinary lira devaluation effect is likely to mask a good deal of significance at the local level (Figures 1 and 5). A substantial interruption of this trend is finally observed for the Northern counties when the existing gap with Central and Southern counties almost disappears giving rise to a more homogenous spatial parameter pattern and hence to loss of statistical significance at the local level.

Significant evidence of local specificity of the business dimension factor (Figures 2 and 6)is also found in most Central and Southern regions, with stronger accentuation of statistical significance in the middle of the decade under more favourable country competitiveness conditions. However, a somewhat critical sensitivity to this factor seems to be prevalent in all

[11] The model fit has been further checked through the computation of the Moran’s I of both global and GWR residuals yielding always no significant autocorrelation values for the latter.

areas, eventually giving rise to a uniform pattern of local parameters and to loss of significance.

Weaker evidence of localised effects is instead found for the district based export propensity which is generally higher for the Centre and the South, particularly in the first part of the decade (Figure 3). Significant spatial parameter patterns arise at the beginning and at the end of the decade only under the specification of the “short-distance” coordinate system which supports the idea of a prominent role of the degree of contextual cohesion due to well structured communication networks.

In 2000 and 2002 a more general tendency of GWR estimates to form homogeneous spatial patterns is found indeed common to all regression parameters, including the damped spatial trend of the intercept term which points out progressive smoothing of local differences in competitiveness conditions (Figure 4).

4.2 Discussion

The analysis presented in this paper shows that the evolution of Italy’s trade competitiveness in the manufacturing sector over the past decade has been deeply affected by important changes of technology based comparative advantages at the local level. The dramatic decrease of Italy’s manufacturing export shares after 1996 goes in fact parallel with a progressive weakening of local competitiveness conditions in the high-tech industries. Despite the stable county-based global relationship found between competitiveness in manufacturing trade and competitiveness in high-tech trade, the emergence of a significant localised relationship brings into evidence the role of counties in Northern regions and that of Western territories in particular. The tendency of the high-tech parameters values to converge to smaller values within northern territories emerges as a clear characteristic of the first part of the decade, while after 1996 a more accentuate process of further convergence to even smaller values involves all Northern counties with respect to Central and Southern counties. The dynamics of this process thus supports the idea that *structural deterioration of Italy’s competitiveness in manufacturing trade started well before the second part of the past decade*. The loss of competitiveness of the North-Western counties has proved to be a determinant factor of this process given the prominent specialisation of these areas in high-tech industries.

The analysis also highlights the specific contribution of the business dimension and the district-based export propensity as structural factors of the so-called *made-in-Italy model* to shaping competitive conditions. However, important differences characterise the influence of these variables compared to the high-tech factor. The global estimate for the business dimension shows in fact a positive trend and local significance for Central and Southern regions, but the increase of the local parameters in Northern regions is substantial at the end of the decade causing loss of significance. *Thus business dimension turns out to be a major bottle-neck for manufacturing trade competitiveness as a whole, while the hypothesis that this process reinforced the progressive weakening of competitiveness in the high-tech trade in Northern territories cannot be ruled out.*

The district based export propensity instead appears to play a marginal role from the local point of view, although some significant results are found for the “short-distance” model specification. This suggests that factors of regional cohesion are indeed prominent for local significance of the district variable. On the other hand the global effect proved to be even greater than that recorded for the high-tech factor and the business dimension, although the sharp downturn after 1998 suggests the idea that a major crisis is on the way.

5. Concluding remarks

The empirical findings presented in this study allowed us to prove the existence of a significant relationship between the evolution of Italy’s manufacturing trade competitiveness and trade performance in high-tech industries according to a dynamic trend deeply rooted at the local level. As a matter of fact, we found that a well grounded relationship between manufacturing trade competitiveness and high-tech trade competitiveness masked important differences between Northern and Central-Southern regions, which eventually disappeared due to progressive decrease of the parameter values in the North. However, other structural factors helped us to interpret the key role of the high-tech variable. The ongoing process of deterioration of the technology based comparative advantages in the North in fact came along with the growing importance of the business dimension factor whose effect turned out to be overwhelming at the local as well at the global level. In this framework the district based export propensity has proved to be a highly significant determinant of the so-called made-in-Italy competitiveness model but only over the period in which the effects on trade competitiveness of the exchange devaluation were strongest. As these effects came to an end, the influence of the district variable also lost its previous strength while still keeping its local specificity.

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Tab. 1. Spatial concentration of exports, 103 counties

	C1						
	1991	1993	1995	1996	1998	2000	2002
High Tech sectors	30.29	30.03	30.43	30.50	25.41	26.07	25.90
Manufacturing sectors	16.56	14.86	14.91	14.28	13.50	13.81	13.97

	C4						
	1991	1993	1995	1996	1998	2000	2002
High Tech sectors	61.75	57.75	59.08	53.97	50.78	46.53	43.48
Manufacturing sectors	31.76	28.64	30.39	29.47	28.05	27.61	27.50

	HEN						
	1991	1993	1995	1996	1998	2000	2002
High Tech sectors	6.33	6.83	6.83	7.07	9.10	9.67	9.68
Manufacturing sectors	20.00	23.21	22.20	23.47	25.45	25.71	25.55

Tab. 2. Regional distribution of exports - NUT 1 Italy's divisions

	High Tech						
	1991	1993	1995	1996	1998	2000	2002
North-West	59.9	58.5	58.3	56.3	47.3	47.3	48.1
North-East	11.1	11.2	12.5	13.7	16.1	18.2	17.6
Centre	20.2	22.9	20.0	21.1	24.9	21.0	23.1
South and Islands	8.9	7.4	9.3	8.9	11.7	13.5	11.2
Italy	100	100	100	100	100	100	100

	Manufacturing						
	1991	1993	1995	1996	1998	2000	2002
North-West	48.9	46.8	46.2	45.3	43.1	41.6	41.3
North-East	26.8	28.5	29.7	30.2	31.0	31.0	31.8
Centre	16.1	16.9	15.2	15.8	16.1	16.7	16.6
South and Islands	8.1	7.8	8.8	8.6	9.8	10.6	10.3
Italy	100	100	100	100	100	100	100

Tab 3. Global Regression results

	1991	1993	1995	1996	1998	2000	2002
R^2 Adjusted	0.257	0.434	0.459	0.471	0.474	0.428	0.466
AIC	267.25	239.22	234.54	232.29	231.57	240.21	233.16
High Tech LCA	0.296**	0.421***	0.279***	0.212***	0.291***	0.380***	0.310***
	(0.087)	(0.075)	(0.075)	(0.075)	(0.072)	(0.076)	(0.072)
Business Dimension	0.274***	0.333***	0.434***	0.450***	0.388***	0.328***	0.368***
	(0.100)	(0.088)	(0.091)	(0.091)	(0.088)	(0.089)	(0.087)
District Export Propensity	0.348***	0.427***	0.410***	0.463***	0.533***	0.304***	0.315***
	(0.165)	(0.145)	(0.151)	(0.150)	(0.149)	(0.089)	(0.086)

*Notes: standard errors in brackets; *statistical significance at the 10% level; ** statistical significance at the 5% level; *** statistical significance at the 1% level*

Tab. 4. Geografically Weighted Regression results - Map Distances

	1991	1993	1995	1996	1998	2000	2002
R^2 Adjusted	0.368	0.454	0.515	0.509	0.524	0.468	0.498
AIC	259.07	238.71	229.59	228.41	225.21	236.74	230.54
High Tech LCA - Median	0.249**	0.411	0.192*	0.196*	0.321**	0.419	0.337
Business Dimension - Median	0.155*	0.279	0.322**	0.331***	0.268***	0.300	0.348
District Export Propensity - Median	0.269	0.437	0.326	0.458	0.572	0.269	0.283*

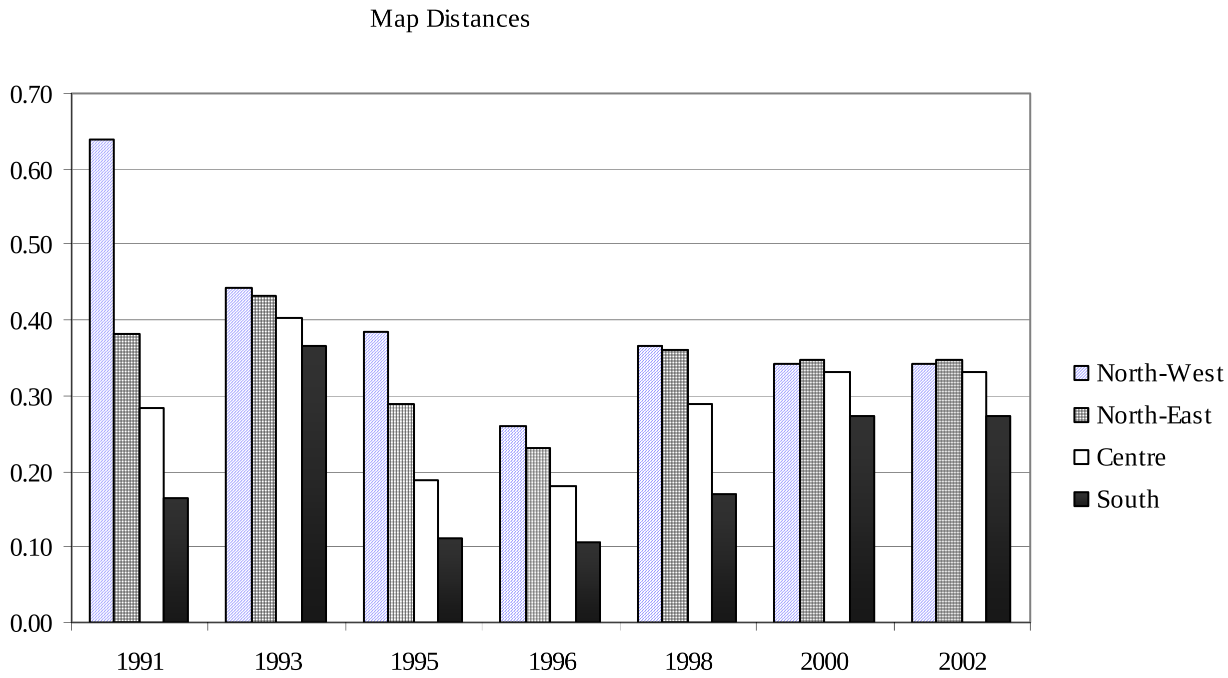
*Notes: * Monte Carlo test statistical significance at the 10% level; ** Monte Carlo test statistical significance at the 5% level; *** Monte Carlo test statistical significance at the 1% level*

Tab. 5. Geografically Weighted Regression results - Short Distances

	1991	1993	1995	1996	1998	2000	2002
R^2 Adjusted	0.378	0.507	0.526	0.521	0.519	0.482	0.502
AIC	257.14	235.73	229.18	230.18	226.31	233.93	229.56
High Tech LCA - Median	0.299**	0.403	0.233**	0.205*	0.316**	0.407	0.331
Business Dimension - Median	0.153	0.204	0.285**	0.255***	0.295***	0.314	0.345
District Export Propensity - Median	0.333*	0.305**	0.271	0.361	0.590	0.261**	0.274*

*Notes: * Monte Carlo test statistical significance at the 10% level; ** Monte Carlo test statistical significance at the 5% level; *** Monte Carlo test statistical significance at the 1% level*

Fig. 1. GWR county based estimates averaged trhoughout Italy's main regional divisions High-tech LCA



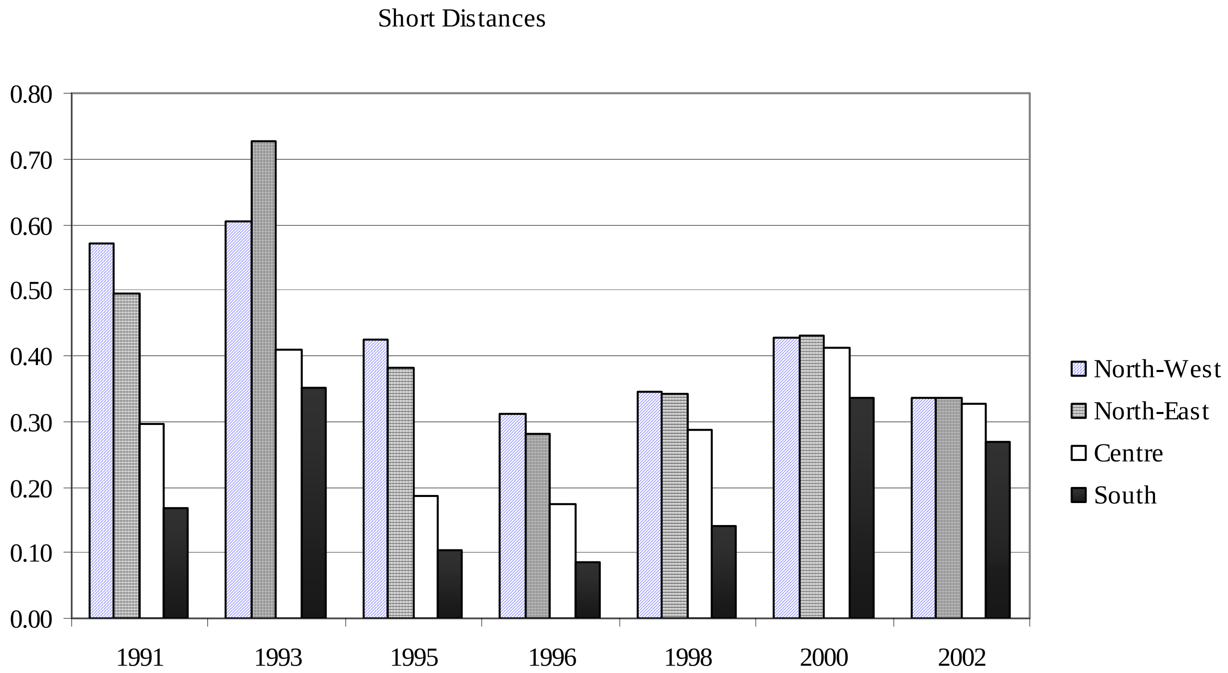
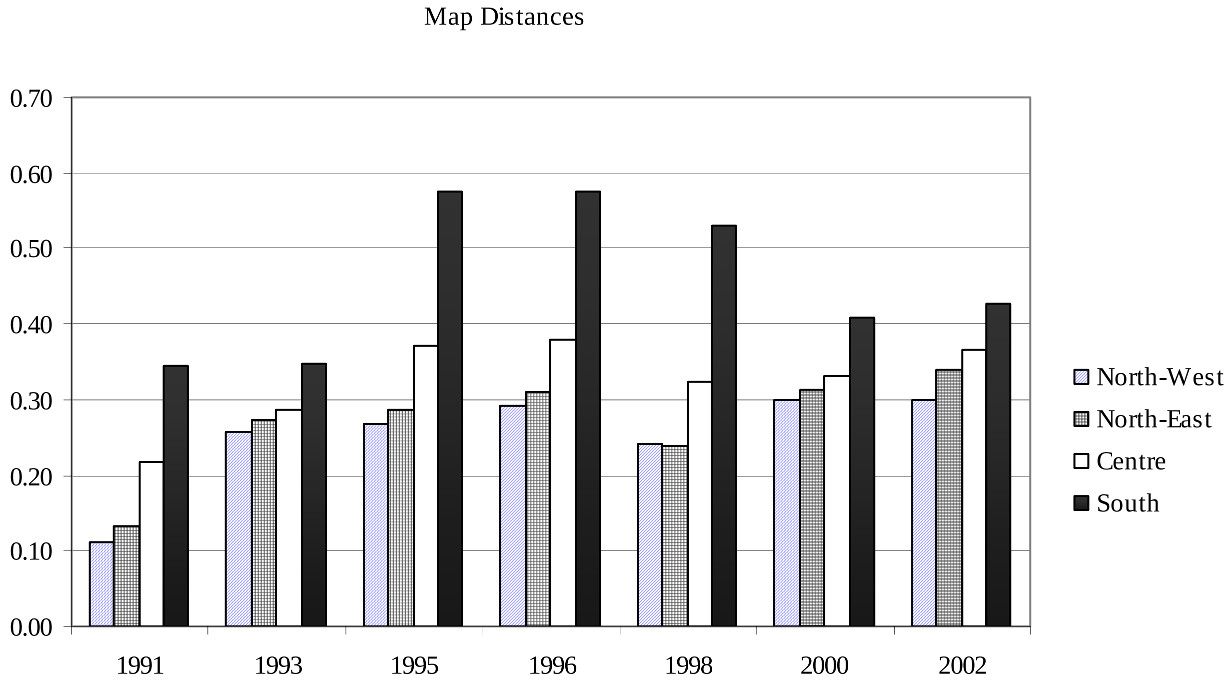


Fig. 2. GWR county based estimates averaged trhoughout Italy's main regional divisions Business dimension



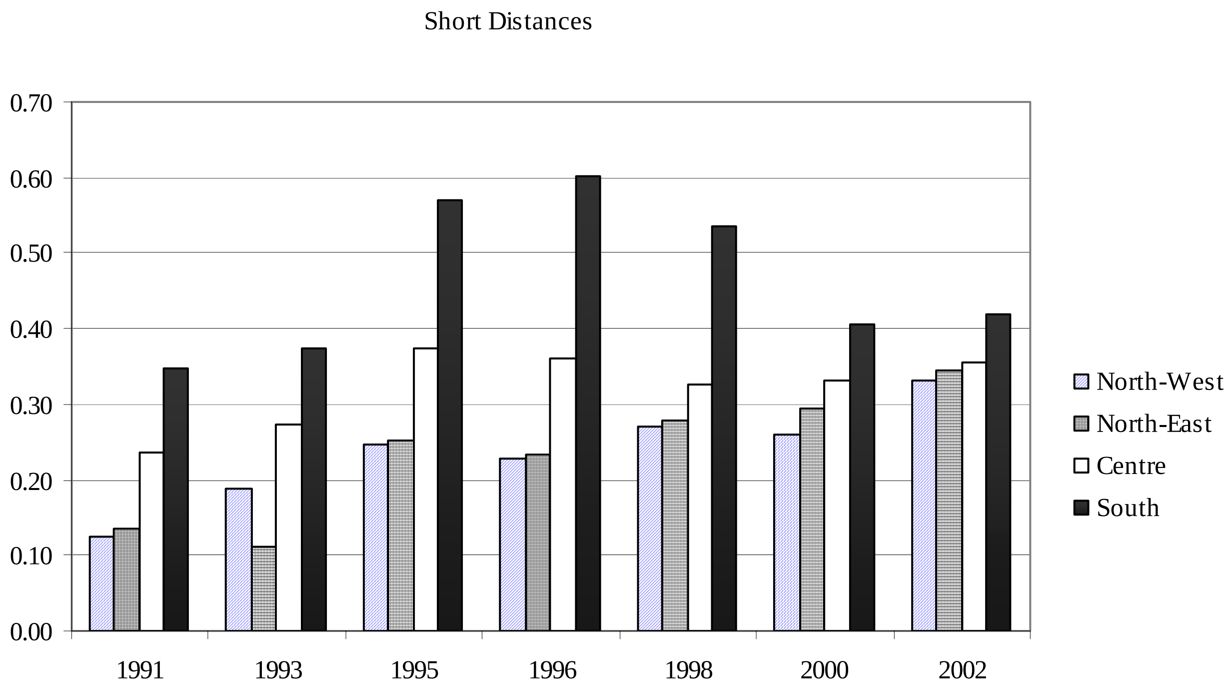
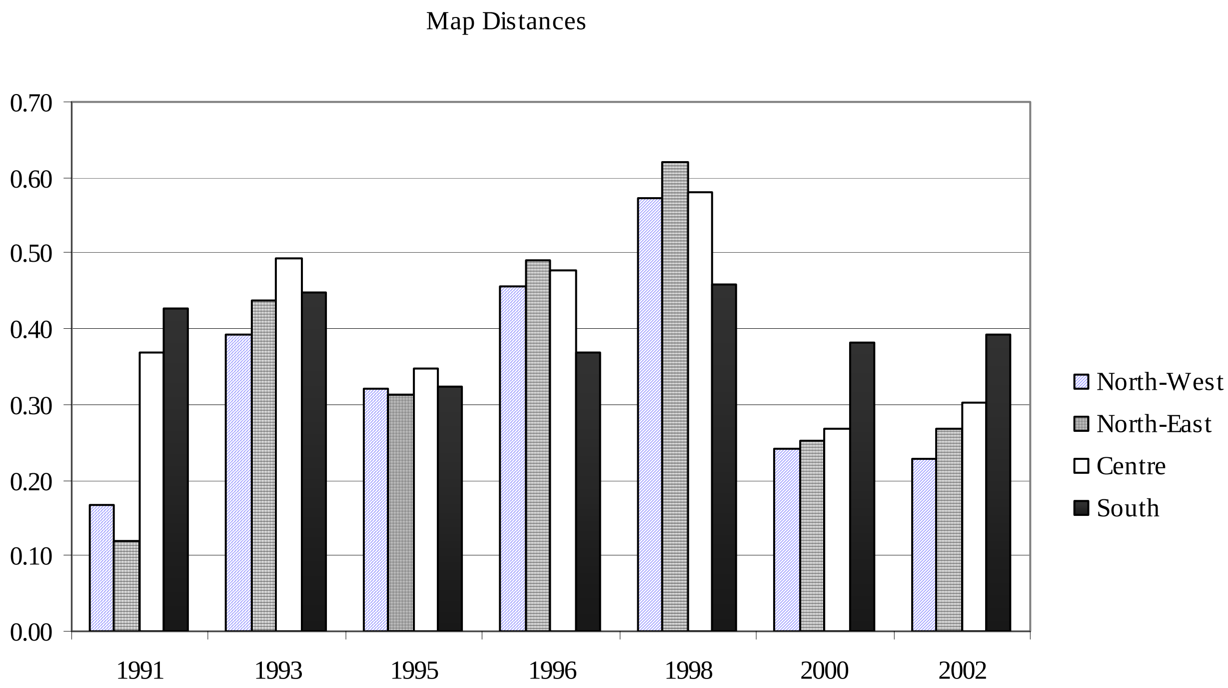


Fig. 3. GWR county based estimates averaged trhoughout Italy's main regional divisions District export propensity



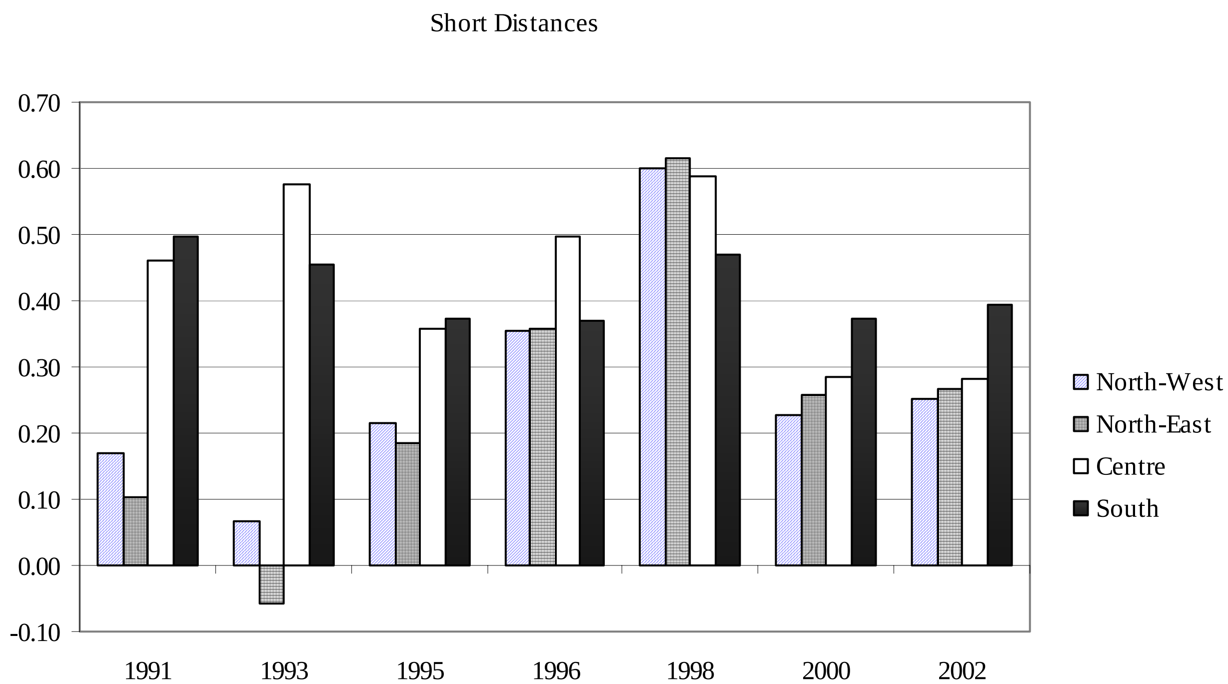
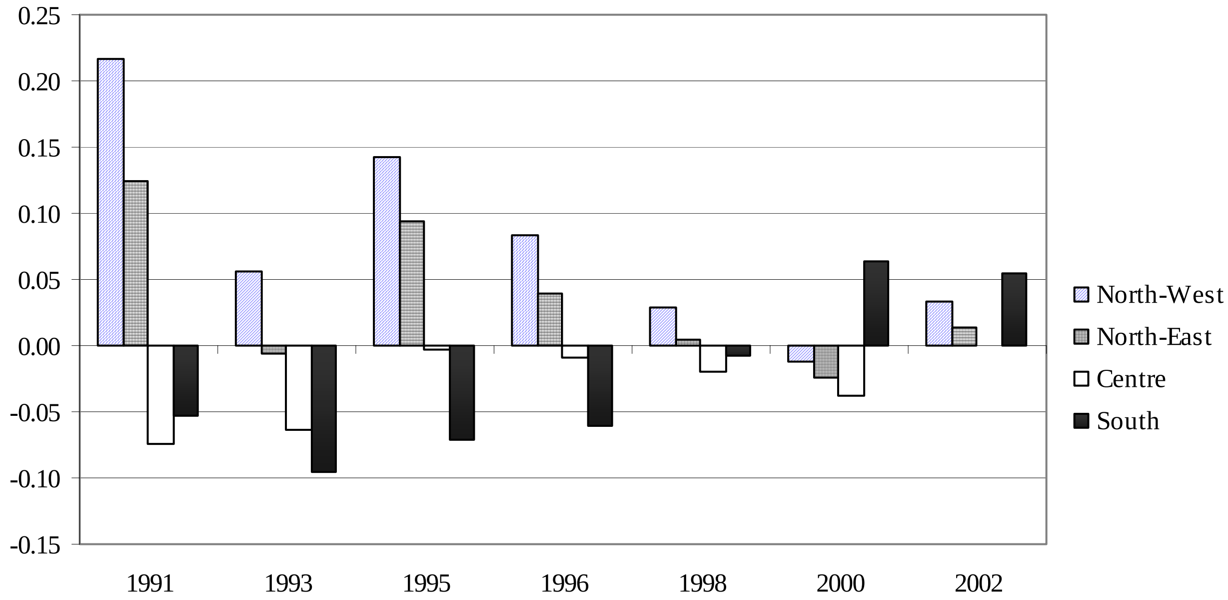


Fig. 4. GWR county based estimates averaged trhoughout Italy's main regional divisions Intercept

Map Distances



Short Distances

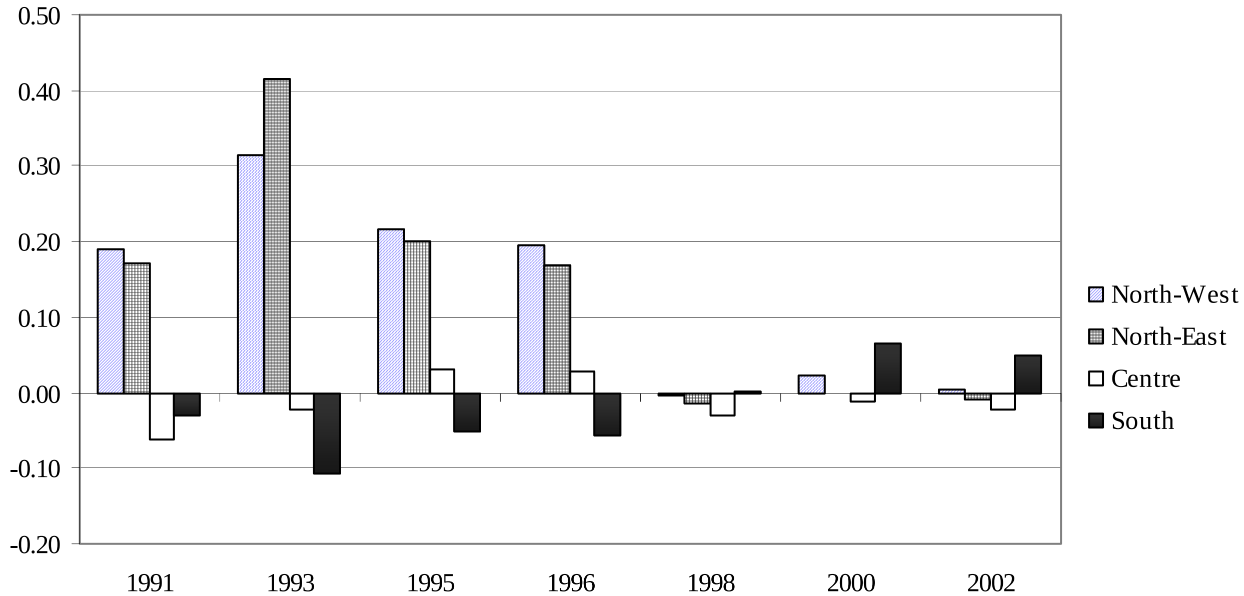
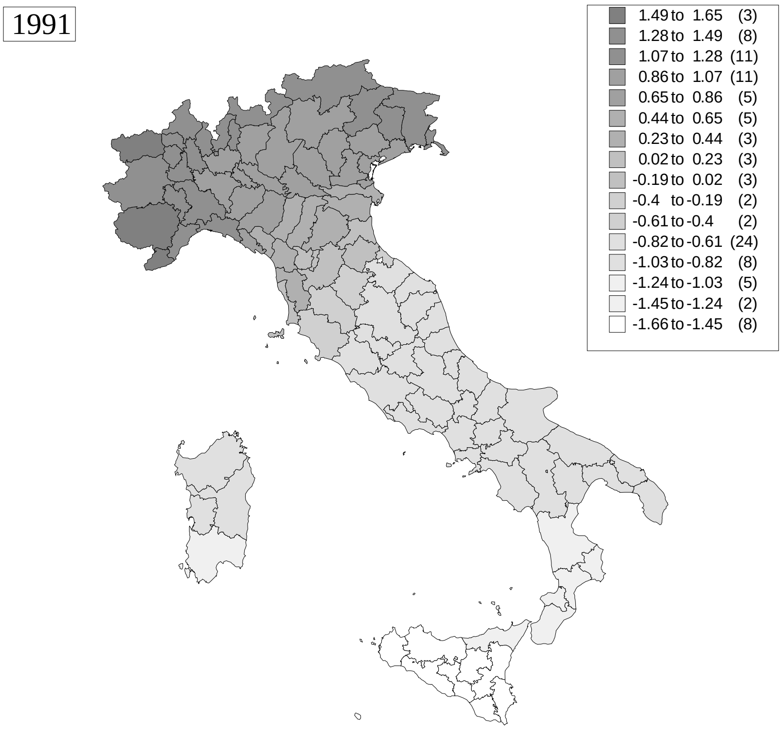


Fig. 5. High Tech LCA estimates county distribution – 1991 and 1998



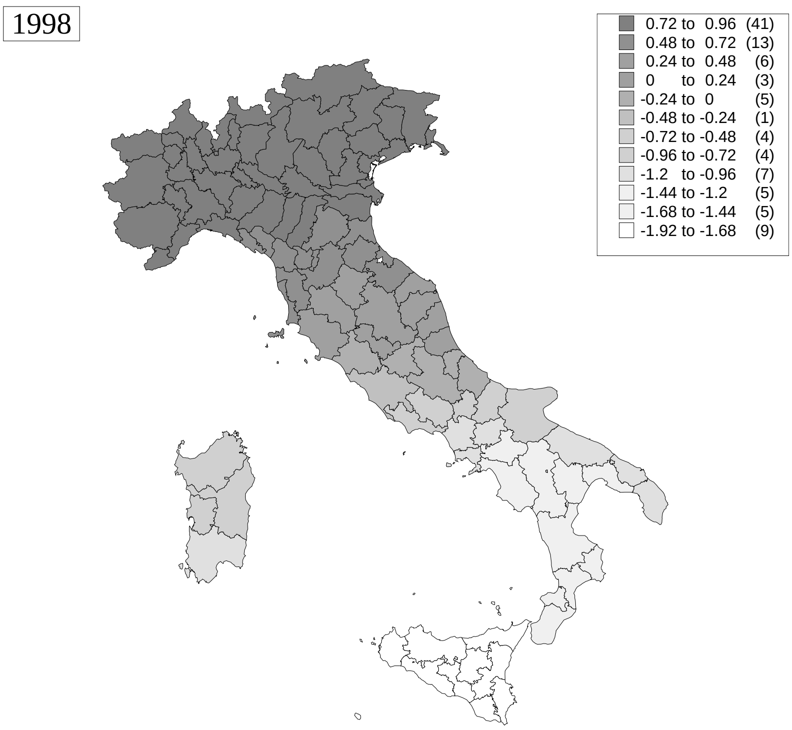


Fig. 6. Business dimension estimates county distribution – 1998 and 2002