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Italian regional specialization: A Spatial Analysis

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This paper tests for the presence and evaluates the effects of spatial interdependencies on Italian regional specialization over the period 1995-2006. We perform exploratory spatial data analysis (ESDA) and estimate a spatial panel data model built according to the NEG theory. ESDA reveals an overall positive spatial interdependence and detect "hot spots" in the North and "cold spots" in the South for all sectors, except for agriculture which shows the reverse. Spatial econometric estimation confirms these results, refuting diffusion of sectoral specialization at country level. The results in terms of specialization determinants are in line with the findings of NEG.

JEL classification: C13, C21, O18, R12

Key words: specialization, new economic geography, exploratory spatial data analysis, spatial econometric analysis.

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1. Introduction

Productive specialization is a widely debated issue in the economic literature, both from the theoretical and empirical angle. Theoretical contributions started with the "traditional trade theory" which argues that, under constant returns to scale and perfect competition hypotheses, productive specialization is driven by comparative advantage. The latter may either arise from differences in exogenous technology (Ricardian models since 1817) or different resource endowments (Heckscher 1919; Ohlin 1933). The economic geography theory subsequently emphasized costs and demand linkages as a key agglomeration force for productive specialization (Fujita 1988; Krugman 1991b; Venables 1996). Models in this strand assume technology's increasing returns to scale and imperfect competition. Finally, another important theoretical strand, originating from the extern economies theory (Marshall 1920), highlights the possibility that knowledge spillovers effects of technology, know-how and information arise in a cluster of industries (Enright 1990).

Most recent empirical contributions to investigating productive specialization have mainly focused on European Union countries (Brülhart 1998; Amiti 1999; Haaland *et al.* 1999; Midelfart-Knarvik *et al.* 2002). The reason is the presence of different effects deriving from the integration process. The latter, in fact, could either stimulate greater specialization, making areas more vulnerable to random demand shifts and asymmetric shocks (Krugman 1991a; OECD 1999; Martin 1999) or lead (through trade intensification) to higher similarity in productive structures and hence progressive synchronization of economic cycles (Helg *et al.* 1995; Frenkel and Rose 1996).

At regional level descriptive analysis has been carried out by Molle (1996), Walz (1999), Hallet (2002), De Siano *et al*. (2005) and Suedekum (2006), amongst others. By contrast, Paluzie *et al*. (2001) for Spain and Combes and Lafourcade (2001) for France go beyond trying to explain the determinants of sector location.

However, none of these studies consider the geographical location of the single region and the possible effects of economic interdependencies among neighboring regions. Indeed, two different kinds of spatial effect may arise. Positive spatial interdependencies enforce more similar specialization patterns through so-called efficiency gains (Venables 2008): intra-sectoral demand/supply linkages and knowledge spillovers. On the other hand, negative spatial interdependencies may generate wider differences among regions due to highly scale-intensive production and high transport costs. Ignoring these effects in the empirical model may produce inefficient estimation results (Elhorst 2009).

Recently, Stirboeck (2006) and Ezcurra *et al*. (2006) filled this gap by using spatial econometric techniques to test for the presence of spatial interaction in productive specialization. Both analyses refer to European regions but come to a different conclusion. Covering the period 1986-1994, Stirboeck finds little evidence of significant economic spatial interdependence effects forcing either a declustering or a polarization process. On the contrary, Ezcurra *et al*. find a positive spatial interdependence of regional specialization, albeit decreasing in absolute value over the sample period (1977-1999). This study, in particular, observes that regions which are more similarly specialized than the EU average, are clustered in the Central area while regions with a different pattern of specialization are located in the European Union Southern periphery.

In line with the above empirical approaches the first aim of our work was to investigate the presence of spatial interdependencies in the development of Italian regional specialization (NUTS2 level, over the period 1995-2006) by means of exploratory spatial data analysis (ESDA) tools (Cliff and Ord 1973, 1981). This approach revealed the presence of two different clusters, one of highly specialized regions in the North (in the South for agriculture) of the country and another of low-specialization regions in the South (North for agriculture). Secondly, we tested for the contribution of spatial effects on the regional productive patterns, estimating a model which refers to New Economic Geography (NEG) specialization determinants, through appropriate spatial econometric techniques (Anselin 1988, 1995; Elhorst 2009). In general, the results show dissimilar movements in the specialization process and the presence of negative spreads of random shock among neighboring regions. To our knowledge, such analyses have not yet been implemented for Italian regions.

The paper is organized as follows. In the second section exploratory spatial data analysis (ESDA) is performed. The third presents the model, data and the spatial econometrics methodology. Spatial econometric results are discussed in Section 4 while Section 5 concludes.

2. Exploratory spatial data analysis

In this section exploratory spatial data analysis (ESDA) is performed in order to assess the presence and features of spatial interdependencies in the specialization patterns of Italian regions (NUTS2 level) in the period 1995-2006. Sectors covered by the study are listed in table 1. As a measure of regional specialization we employ the Balassa index based on regional sector employees[1]:

$$SP_{is} = \frac{\dfrac{E_{is}}{\sum_{s=1}^{n} E_{is}}}{\dfrac{\sum_{i=1}^{m} E_{is}}{n\sum_{s=1}^{n}\sum_{i=1}^{m} E_{is}}} \qquad (1)$$

where E_{ij} indicates the number of employees in region *i* and sector *s*. Basic descriptive statistics presented in table 2 show that sectoral specialization varies considerably among region while it remains quite stable over time. With a view to completing the descriptive analysis of the dynamics of the specialization indexes we built a ten percentile transition matrix for each sector obtaining the probability of each region changing its specialization over time. Mobility across sectors is then evaluated calculating the following Shorrock Mobility Index (SMI):

$$SMI= [n-tr(TM)]/(n-1) \qquad (2)$$

where n is the number of classes. A value of *SMI* equal to *0* indicates the absence of mobility (persistence of specialization) while SMI equal to $n/(n-1)$, 1.11 in our analysis, indicates the highest

[1] Data on sectoral and total employment are taken from ISTAT- *Regional Economic Accounts*, 1995 to 2006.

mobility. SMI results, presented in table 2[2], show a high persistence of specialization for all sectors except for trade and tourism. Among the aggregated sectors, agriculture shows a higher persistence than industry and services.

Using ESDA the existence of both global and local spatial autocorrelation of regional specialization can be revealed and evaluated. Global spatial autocorrelation analysis aims to test for the presence of potential clusters of high/low specialization regions. Local spatial autocorrelation analysis goes beyond locating the clusters, measuring their spatial extent and identifying the regions which contribute more to global autocorrelation.

Global spatial clustering

Global spatial tools are single statistics summarizing regional spatial pattern. To test for the presence of spatial autocorrelation we employed the following global Moran Index (I_s^t) (1948):

$$I_s^{\,t} = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \, (SP_{i,s}^{\,t} - \overline{SP}_s^{\,t})(SP_{j,s}^{\,t} - \overline{SP}_s^{\,t})}{S_0 \sum_{i=1}^{n} (SP_{i,s}^{\,t} - \overline{SP}_s^{\,t})^2} \qquad (3)$$

where *i* indicates the single region and *j* refers to its neighbours, $\overline{SP}_s^{\,t}$ represents the sample mean estimate of the specialization index of sector *s* at time *t*, w_{ij} is the spatial weight matrix **W** element relative to regions *i* and *j*, and $S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$.

Following Le Gallo and Ertur (2003), we used a row-standardized weight matrix computed on the *k*-nearest regions, whose weights are given by the inverse distance among regional administrative centers (regional capitals)[3]. This type of matrix is preferred over contiguity and adjacent ones due to the presence of islands in the sample, which would otherwise be automatically excluded in a different matrix, the possibility of considering the connections among regions

[2] Transition matrices relative to each sector are available upon request from the authors.
[3] It is assumed (Stirboeck 2006) that administrative centers correspond to the economic centers.

belonging to different geographical areas and, finally, the selection of the same number of neighbors for each region. Since the diagnostics tests depend on the distance matrix, the robustness of the results must be controlled for different *k*. In this study we performed ESDA for 6, 10 and 14 nearest regions. Given that the results do not change we will present only those referring to the six nearest regions[4].

The expected value of the Moran index (E(I)) is equal to $-1/(n-1)$. Values of I_s^t greater than the expected value indicate positive spatial autocorrelation, which means that regions with high (low) specialization in a specific sector are located close to other regions with high (low) specialization in the same sector. Values of I_s^t smaller than the expected values point to a negative association, and hence a dissimilar specialization, between nearby regions.

We calculated the Moran indexes for all the sectors objective of the analysis. However, table 3 presents the results only for those sectors for which significant values were found, namely agriculture, industry, strictly industry, manufacturing, machinery, paper, metal, wood and tourism. The evidence is of an overall positive autocorrelation. The dynamic shows that the index does not change significantly over time, for industry, strictly industry, manufacturing and machinery, revealing a tendency towards geographical clustering, while it declines in agriculture, metal, paper, wood and tourism, indicating a tendency to greater diffusion of the relative activities.

Local spatial clustering

Local methods of spatial clustering analysis consider the relationship between each region and its neighbors, picking out specialization hot spots (high-value clusters) and cold spots (low-value cluster). In our study the presence of local spatial autocorrelation is tested through two different tools: the Getis-Ord statistic (Getis and Ord 1992; Ord and Getis 1995; Sokal *et al.* 1998) and the Moran scatterplot (Anselin 1996).

[4] All the results are available upon request.

The Getis-Ord test refers to the concentration of specialization index values in the neighborhood of a region i. The original statistic is the following:

$$G_{i,s} = \frac{\sum_{j=1}^{n} w_{ij} SP_{j,s}}{\sum_{j=1}^{n} SP_{j,s}} \qquad \text{with } j \text{ not equal to } I \tag{4}$$

where w_{ij} is the corresponding element of a non-standardized symmetric binary weights matrix which attributes 1 to the *k*-nearest regions and 0 to the others and to the pivot region. Once standardized, positive values of $G_{i,s}$ indicate spatial clustering of high specialized regions around region *i* in the correspondent sector, while negative values indicates a cluster of low specialized regions.

We find a consistent difference in the initial specialization level between Northern and Southern regions, as shown in the maps (figures 1-16). Agriculture is the only sector displaying a specialization hot spot in the Centre-South of the country (9 regions) and a “cold spot” in Northern regions (8 regions). Industry, its sub-sectors and branches show the reverse. In particular, for industry, strictly industry, manufacturing and machinery a cluster of highly specialized regions is located in the North (7 regions)[5]. Central regions mainly do not present significant values for these sectors and Southern regions form significant spatial clusters of low specialization. Few differences are found for paper and wood clusters, compared with the previous ones. The sector that shows the highest difference between Northern (7 high specialization) and Southern regions (9 low specialization) is that of metal.

The specialization dynamic over the period 1995-2006 shows an overall persistence of high and low value clusters. Figures 1-16 display initial and final year significance maps, at 10% significant level, for those sectors with significant regional $G_{i,s}$ statistics. Initial and final year maps are the same except for a few Central and Northern regions which lose significance at the end of the sample period.

[5] Valle d’Aosta belongs to this cluster only for Industry and Machinery while Marche is not significant in Machinery.

The second measure of local spatial clustering implemented in our study is the Moran scatterplot (Anselin 1996) which plots, for each region, the spatial lag of the specialization index[6] versus its unit value. The four quadrants of the scatterplot indicate different types of spatial association. The upper right and lower left quadrants show clustering of high and low specialization values, respectively. The remaining quadrants display regions with a negative spatial association (dissimilar regions). Figures 17-32 display the Moran scatter plots for those sectors that present a higher number of significant values of the local Moran index for the initial and final year. Regarding the aggregated sectors, agriculture and industry show positive spatial associations while services shows no significant value. In detail, while agriculture presents clusters of high specialization in Southern regions (35%) and clusters of low values in Northern regions (50%), industry shows the reverse (40% in high specialization clusters and 35% in low). The only significant change is the increase in industry specialization in Molise and Basilicata which move from the lower left to the lower right quadrant. For the sub-sectors of industry and manufacturing as well, we find a similar spatial association with highly specialized clusters including mainly Northern regions and low specialization regions localized in the South of the country. There are few regions in the other two quadrants to detect different spatial regimes.

In synthesis, study of global spatial autocorrelation highlights an overall positive spatial interdependence for regional specialization. Local spatial autocorrelation indexes go beyond highlighting specialization hot spots in Italy's Northern regions and "cold spots" in the South, except for agriculture that shows the reverse. Therefore, our study finds broad differences between specialization in the Centre-North and South of the country.

3. Sectoral specialization: spatial econometrics approach

3.1 Model specification and dataset

[6] The spatial lag is the spatially weighted average of the values at neighboring units.

ESDA analysis reveals the presence of significant spatial interaction in agriculture, industry, strictly industry, manufacturing, machinery, paper, metal, wood and tourism. Hence we carry out the study on these sectors by testing and evaluating the spatial interaction effects on regional specialization estimating an empirical model through spatial panel techniques. To this extent we introduce a spatial component into a model which detects the determinants of regional structure of production. Again, our sample is given by all Italian regions (NUTS2 level) in the period 1995-2006.

The choice of the explicative variables of our empirical model is suggested mainly by NEG theory (Krugman 1991a; Combes and Overmann 2004). First of all, as highlighted by Krugman (1991a) and Fujita and Thisse (2002), we consider the link between market proximity and industrial location. This relationship, which accounts for the effects of transport costs on the decision of a firm's geographical location, has been emphasized since Harris (1954). Of course, the higher the transport cost the lower the possibility of a firm to locate its activity in a given region. Harris measured accessibility to the correspondent market, namely the market potential (MP), with the sum of a measure of the economic activity in all other regions weighted by the inverse of the distances between regions. In our study we build the market potential using the GDP level as a measure of economic activity.

Trade theories, arguing the importance of market integration for the specialization of economies, emphasize the role of economic openness as one of the main determinants of the productive structure. As a measure of economic openness (OPEN) we introduce an indicator given by the ratio of the sum of exports and imports to GDP.

The concentration of economic production exhibiting increasing returns to scale in a given region may also be induced by the presence of scale economies. The latter, enforcing the competitive position of firms, contribute to determining their decision on where to locate and hence the structure of regional specialization. Following Brun and Renard (2001) our scale economies index (SE) is given by the ratio of the sum of the added values from the five chief sectors in each region to its total added value. Besides, in order to control for some regional characteristics we introduce size, per capita GDP and a measure of research intensity as explicative variables.

From a theoretical point of view, the relationship between the size of a region, measured by its population (POP), and its productive specialization is generally inverse. Indeed, since Ullman and Dacey (1960) it has been assumed that greater heterogeneity in consumer preferences, occurring in larger regions, induces lower specialization. Later, following NEG (Fujita *et al.*1999; Fujita and Thisse 2002), this relation was confirmed on the basis that agglomeration economies generally enforce diversification in larger regions: the larger the size of a market the greater is its industrial variety. However, this theory argues that if agglomeration economies were sector-specific they would increase the level of specialization. As specialization is also known to be affected by the development level, among the explicative variables we include regional per capita GDP (GDP). In a previous study (De Siano, D'Uva 2006), in fact, we already found a positive relationship between the initial GDP level and the specialization in more advanced sectors.

Finally, we construct a proxy of research intensity using research and development expenditure over GDP (RI). The use of R&D expenditure at regional instead of sectoral level is forced by lack of data[7]. Therefore the model we estimate is the following[8]:

$$SP_{it}^{s} = \beta_1 MP_{it} + \beta_2 SE_{it} + \beta_3 OPEN_{it} + \beta_4 POP_{it} + \beta_5 GDP_{it} + \beta_6 RI_{it} + \varepsilon_{it} \qquad (5)$$

3.2 Econometric methodology

The spatial econometrics literature distinguishes two different ways of modeling spatial interaction (Anselin 1988; Elhorst 2009):

[7]The use of other measures, such as the number of patents, was not possible because relative data are unavailable for our sample period.

[8] Data used to build all the explicative variables are taken from ISTAT- *Regional Economic Accounts* and *Resources and Employment Accounts*, 1995 to 2006.

- Spatial autoregressive models (SAR), when the dependent variable is influenced by the dependent variable observed in the neighbouring regions (spatial lag dependence). In this case equation (5) would be modified as follows:

$$Sp_{it}^{s} = \delta \sum_{j=1}^{N} w_{ij} Sp_{it}^{s} + \beta_1 MP_{it} + \beta_2 SE_{it} + \beta_3 OPEN_{it} + \beta_4 POP_{it} + \beta_5 GDP_{it} + \beta_6 RI_{it} + \mu_i + \varepsilon_{it} \qquad (6)$$

where s indicates the sector, w_{ij} is the single element of the row-standardized distance weight matrix computed on the *k*-nearest regions[9] and μ_i the regional specific effects. A positive δ coefficient would indicate similar movements among neighboring regions' specialization, while a negative value suggests differences with respect to neighbors' specialization.

- Spatial error models (SEM), when error terms are correlated across space (spatial error dependence). Equation (5) in this case would become:

$$SP_{it}^{s} = \beta_1 MP_{it} + \beta_2 SE_{it} + \beta_3 OPEN_{it} + \beta_4 POP_{it} + \beta_5 GDP_{it} + \beta_6 RI_{it} + \mu_i + \phi_{it} \qquad (7)$$

$$\varphi_{it} = \rho \sum_{k=1}^{N} w_{ik} \varphi_{it} + \varepsilon_{it} \qquad (8)$$

A significant parameter ρ indicates that a random shock in a spatially significant omitted variable that affects specialization in a region will also extend to its neighbors.

In order to choose the proper spatial panel econometric model for each sector (Anselin *et al.* 2006; Elhorst 2009) we perform the robust Lagrange-Multiplier tests, for spatial interaction on equation (5), namely the robust-LM*lag* and the robust-LM*err* tests. The null hypothesis of these tests is the absence of spatial dependence. The alternative hypotheses are, respectively, the presence of spatial lag and spatial error dependence. We choose the model specification which results to be significant. If both null hypotheses are rejected, as suggested by Anselin (1992) and Florax *et al.*

[9] See section 2 for **W** construction.

(2003), we estimate the model using the more significant specification (highest value of the robust-LM).

The endogeneity induced by the spatial lag, in the SAR model, and the presence of autocorrelation in the error component, in the SEM model, violate the hypotheses of the standard regression model. Therefore, as suggested by the empirical literature (Anselin 1988, Anselin and Hudak 1992, Elhorst 2009), both model specifications will be estimated through the Maximum Likelihood procedure.

These two different spatial panel specifications will be estimated by a time-fixed effects model. The choice of a fixed effects model instead of a random one is due to the fact that our panel includes the totality of Italian regions and not a sample of them (Elhorst 2009). Besides, the use of a "time"-fixed model derives by the low variability of the dependent variable (Elhorst 2009), that is a persistence of the specialization in each sector as showed by the Shorrocks Mobility indexes (Table 1).

The model specified in equation (5) will be estimated through a spatial panel with time-fixed effects. The choice of a time-fixed effects model, as stated by the theory (Elhorst 2009), is suggested by the presence of a period (T=12) which is not sufficiently large and by a small variation in the dependent variable (specialization index) over time. The small variability of regional specialization over time is evidenced by the low values of the Shorrocks Mobility indexes as shown in table 1.

4. Spatial econometric results

In this section we present the results of the spatial econometric procedure. We computed this analysis only for those sectors (12), namely agriculture, industry, strictly industry, manufacturing, paper, machinery, mineral, wood, leather, textile, metal and tourism, for which global and/or local spatial statistics revealed the presence of spatial interdependencies.

First, we performed the analysis using an inverse distance weight matrix based on the six nearest regions. Then, in order to check the robustness of our results, we replicated the estimates using the 10 and 14 nearest regions. As the results are robust with regard to the choice of the spatial weight matrix, we present only the outcome relative to analysis of the six nearest regions[10].

Table 4 presents the robust LM*lag* and LM*err* tests results. We find significant spatial interaction of regional specialization for industry, strictly industry, manufacturing, machinery, wood, leather and tourism. In particular, the tests suggest a spatial autoregressive specification of the specialization model for industry, machinery, wood and tourism and a spatial error specification for strictly industry, manufacturing and leather.

We present the estimation results of the spatial panel models in table 5 . SAR model results reveal the presence of significant positive spatial effects in the wood sector, indicating similar movements in the specialization process among neighbouring regions. A negative coefficient is found for tourism, as expected. In fact, tourism services are mainly linked to the endowments of the region itself in terms of natural resources and environmental characteristics. Finally, industry and machinery do not present significant spatial effects.

Spatial error model estimation presents a negative coefficient ρ for strictly industry, manufacturing and leather. This may indicate that a random shock occurring in a given region affects its neighbors negatively.

On the whole, these results are in line with the outcome of ESDA which highlights the presence of two different clusters, one of highly specialized regions in the North of the country and another of low specialization regions in the South, rather than an overall diffusion of sectoral specialization. Besides, as regards the determinants of regional specialization, econometric analysis shows that specialization increases with economic openness and market proximity, in accordance with NEG theory. The negative impact of market potential on tourism and wood is probably due to the fact that, for regions specializing in these sectors, market accessibility may be negligible with

[10] Other results are available upon request.

respect to the specific resource endowments. Scale economies have a negative impact on regional specialization, except for tourism. A possible explanation may be the fact that scale economies are not sector-specific and, at a national level, sector growth takes place at the expense of other sectors.

The negative and significant sign of population coefficients in all the sectors indicates that regional size enforces greater industry variety, as suggested by the majority of the theoretical literature. As a consequence, the agglomeration economies arising in the region are not sector-specific. The coefficient of the per capita GDP level is negative, suggesting that the specialization level in industry, its sub-sectors and branches increases in relatively poor regions.

The outcome relative to the research intensity level reveals a negative impact on specialization. This may be due to the fact that our explicative variable is not at the sectoral level as indicated in the previous section.

Above results are robust with regard to the choice of the spatial weight matrix.

5. Conclusions

Econometric theory has recently highlighted the importance of considering spatial interdependencies in model estimation (Anselin 1988, 1995; Elhorst,2009). Indeed, ignoring spatial interdependencies, if present, may lead to inefficient results.

The main purpose of this paper was to test the presence of spatial interdependencies and, further, to evaluate their effects on Italian regional specialization patterns over the period 1995-2006. For this purpose, we first performed exploratory spatial data analysis (ESDA) and then estimated a spatial panel data model built according to the NEG specialization determinants. To our knowledge, such analyses have never been implemented for Italian regions.

ESDA, by means of global and local spatial statistics, reveals an overall positive spatial interdependence for regional specialization and highlights broad differences between the Centre-North and South of the country. In particular, local spatial autocorrelation picks out specialization hot spots in Italy's Northern regions and "cold spots" in the South, except for agriculture. The latter sector presents a highly specialized cluster in Southern regions (35%) and a low specialization cluster in the North (50%); industry shows the reverse (40% in high specialization clusters and 35% in low). In industry sub-sectors and branches we find a spatial similar association to their aggregate sector. Furthermore, dynamic analysis of specialization shows overall persistence of high- and low-value clusters over the considered period. This picture is confirmed by spatial econometric estimation which refutes diffusion of sectoral specialization at country level.

Turning to the determinants of regional specialization included in the empirical model, the estimates of the coefficient show the expected signs. In particular, we find that openness and market proximity have a positive influence on specialization in line with the findings of the NEG. Besides, larger regional size seems to induce a greater variety in industry, meaning that agglomeration economies are not sector-specific.

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Fig. 1: $G_{i,s}$ *significance map for Agriculture Balassa Index 1995*

Fig. 2: $G_{i,s}$ *significance map for Agriculture Balassa Index 2006*

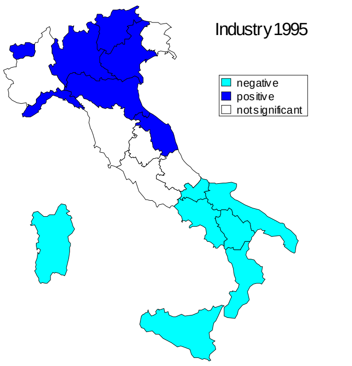

Fig. 3: $G_{i,s}$ *significance map for Industry Balassa Index 1995*

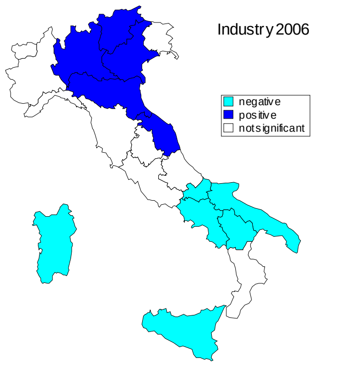

Fig. 4: $G_{i,s}$ *significance map for Industry Balassa Index 2006*

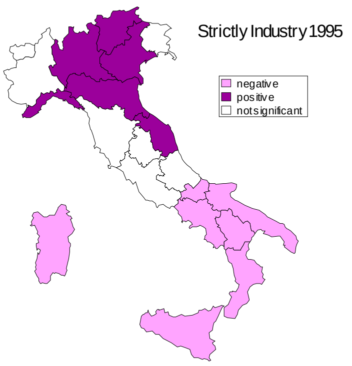

Fig. 5: $G_{i,s}$ *significance map for Strictly Industry Balassa Index 1995*

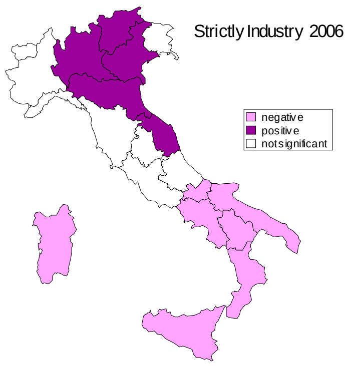

Fig. 6: $G_{i,s}$ *significance map for Strictly Industry Balassa Index 2006*

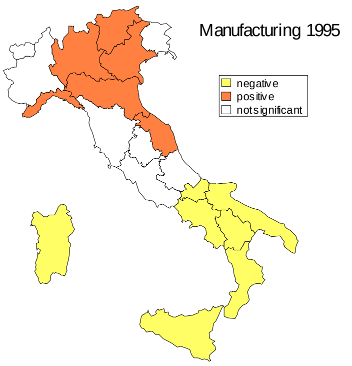

Fig. 7: $G_{i,s}$ *significance map for Manufacturing Balassa Index 1995*

Fig. 8: $G_{i,s}$ *significance map for Manufacturing Balassa Index 2006*

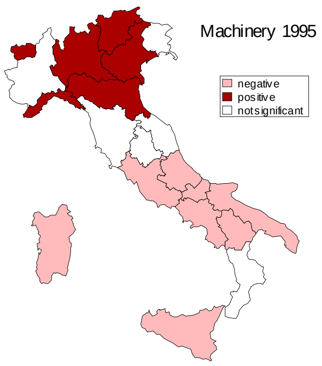

Fig. 9: $G_{i,s}$ *significance map for Machinery Balassa Index 1995*

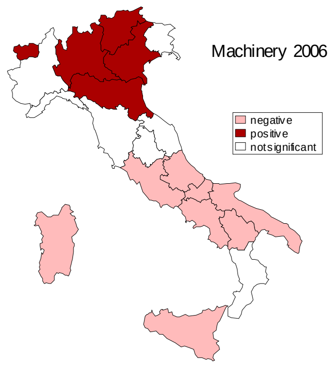

Fig. 10: $G_{i,s}$ *significance map for Machinery Balassa Index 2006*

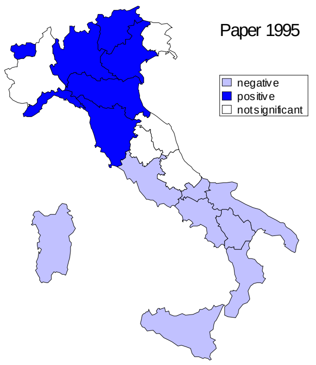

Fig.11: $G_{i,s}$ *significance map for Paper Balassa Index 1995*

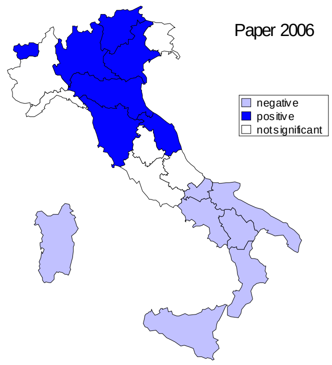

Fig. 12: $G_{i,s}$ *significance map for Paper Balassa Index 2006*

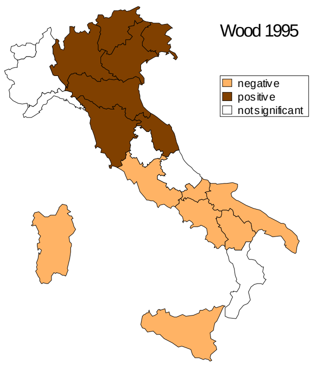

Fig. 13: $G_{i,s}$ *significance map for Wood Balassa Index 1995*

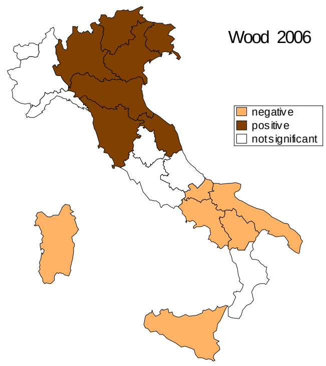

Fig. 14: $G_{i,s}$ *significance map for Wood Balassa Index 2006*

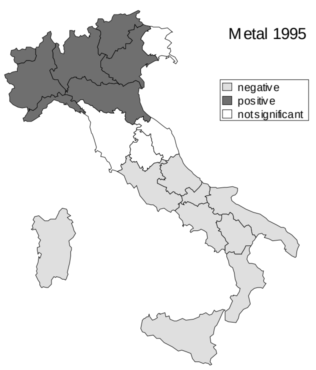

Fig. 15: $G_{i,s}$ *significance map for Metal Balassa Index 1995*

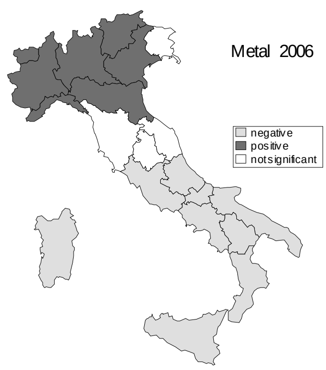

Fig.1 6: $G_{i,s}$ *significance map for Metal Balassa Index 2006*

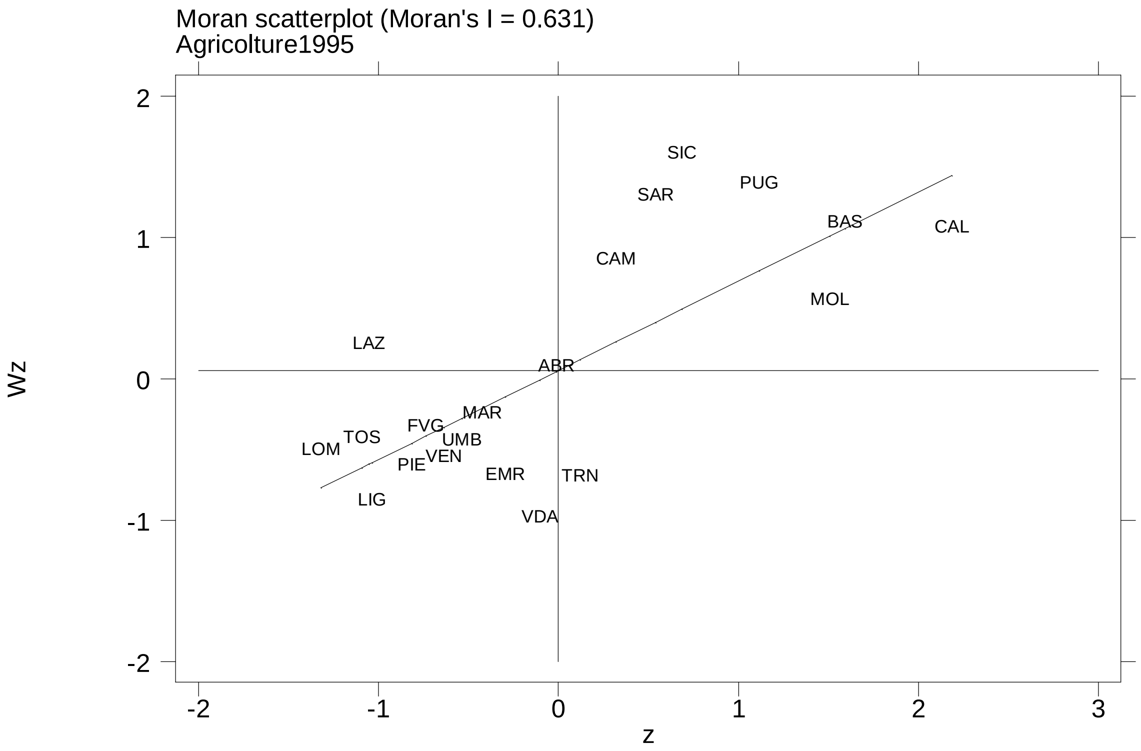

Fig. 17: *Moran scatter plot for Agriculture Balassa Index 1995*

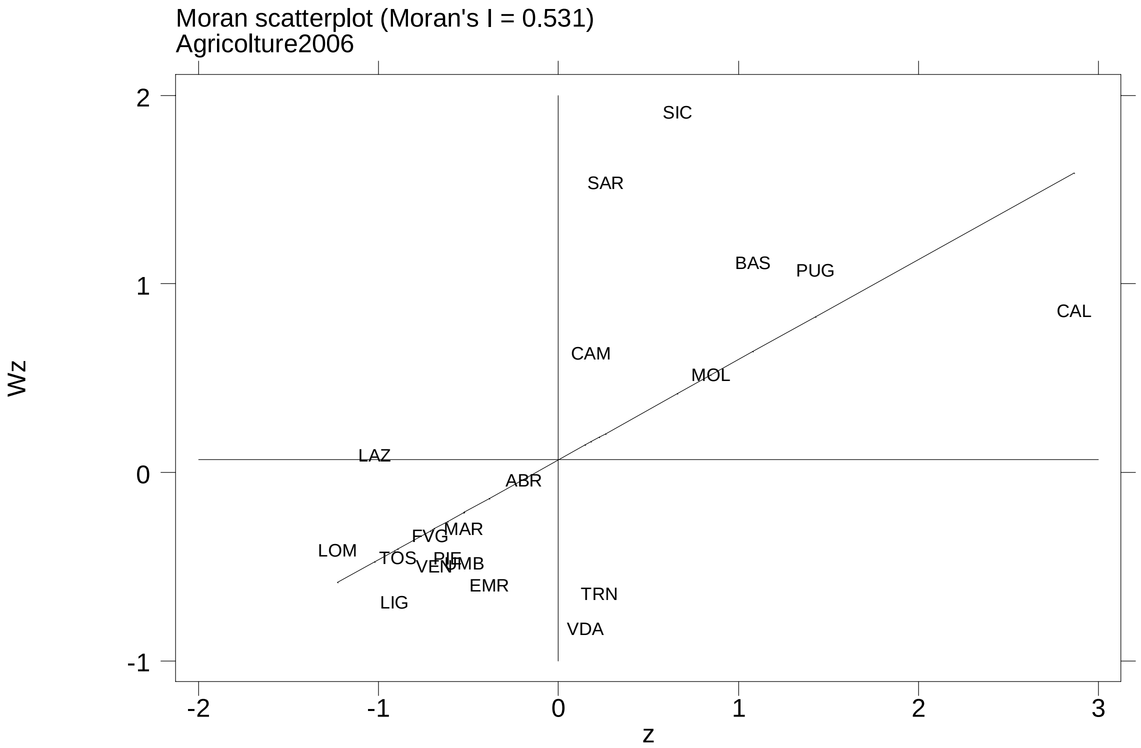

Fig. 18: *Moran scatter plot for Agriculture Balassa Index 2006*

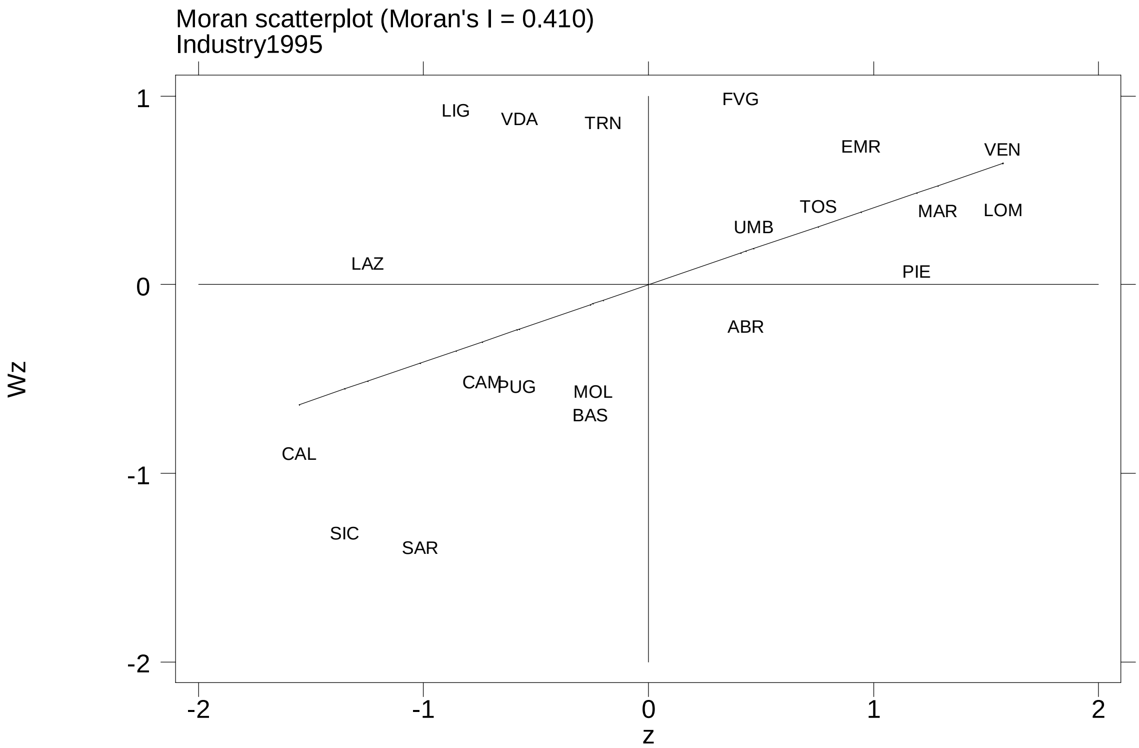

Fig. 19: *Moran scatter plot for Industry Balassa Index 1995*

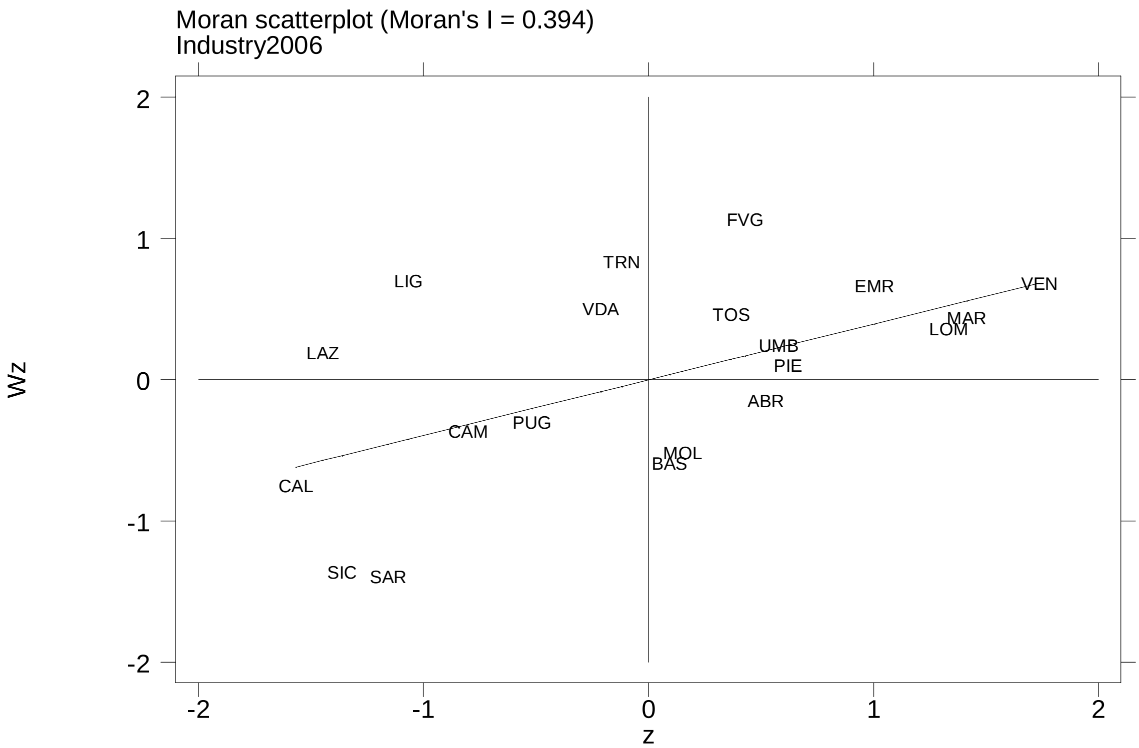

Fig. 20: *Moran scatter plot for Industry Balassa Index 2006*

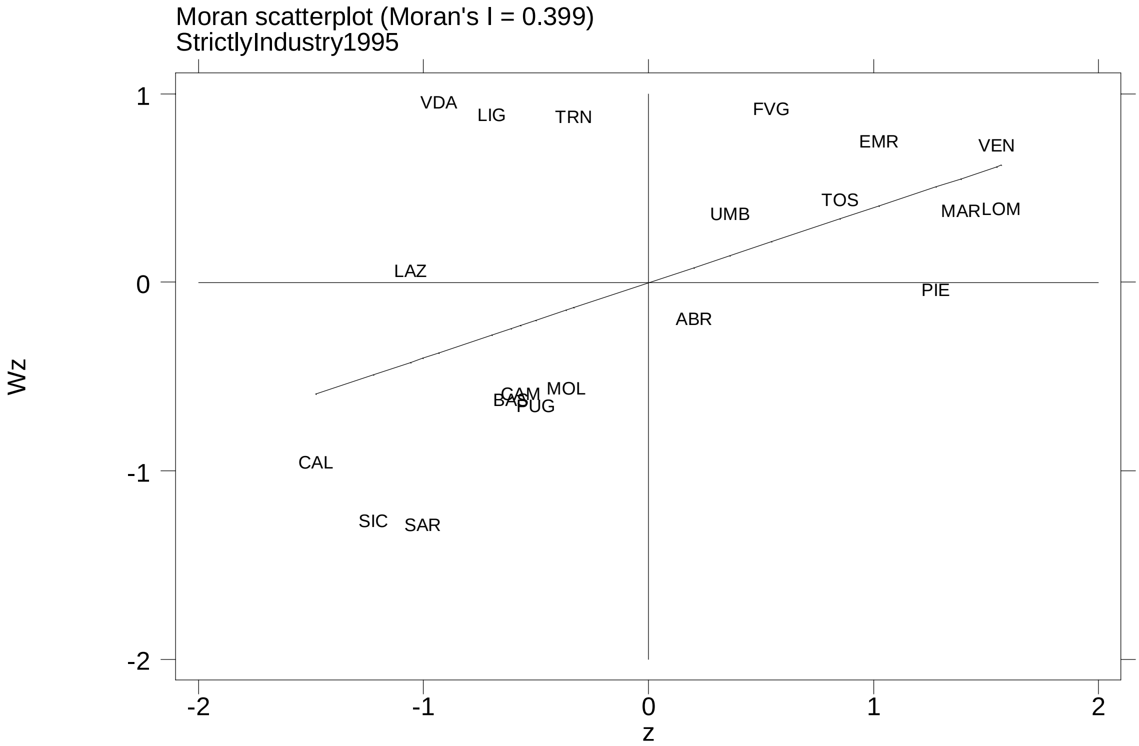

Fig. 21: *Moran scatter plot for Strictly Industry Balassa Index 1995*

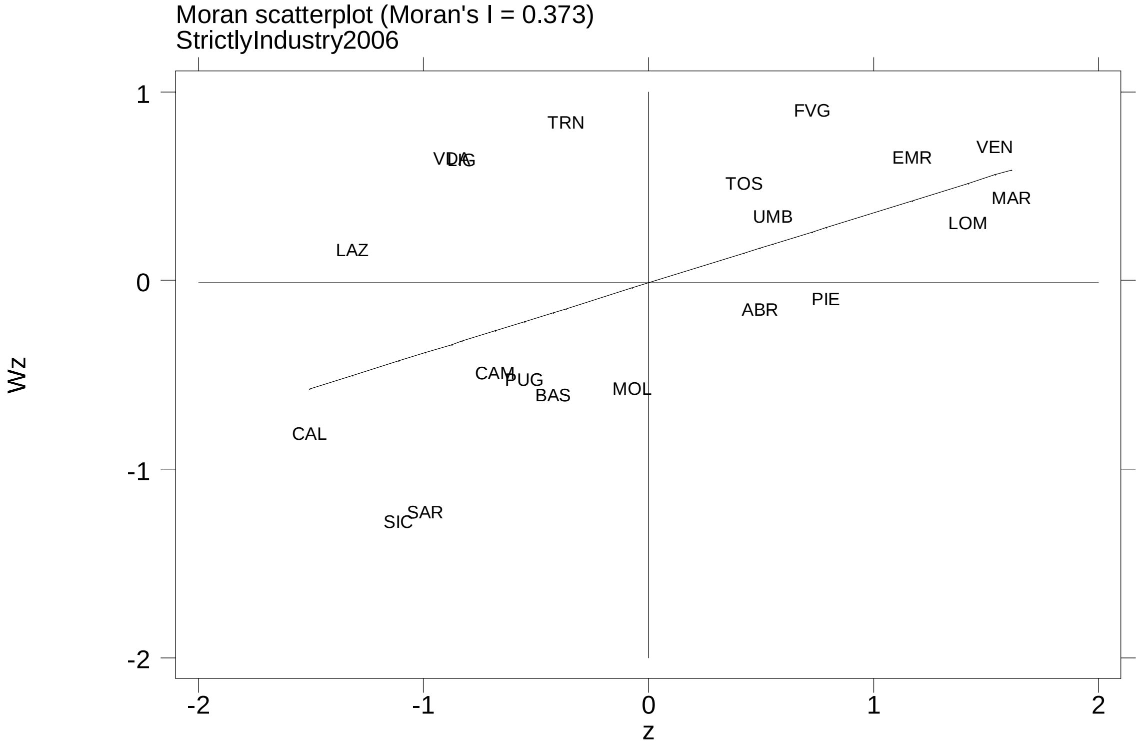

Fig. 22: *Moran scatter plot for Strictly Industry Balassa Index 2006*

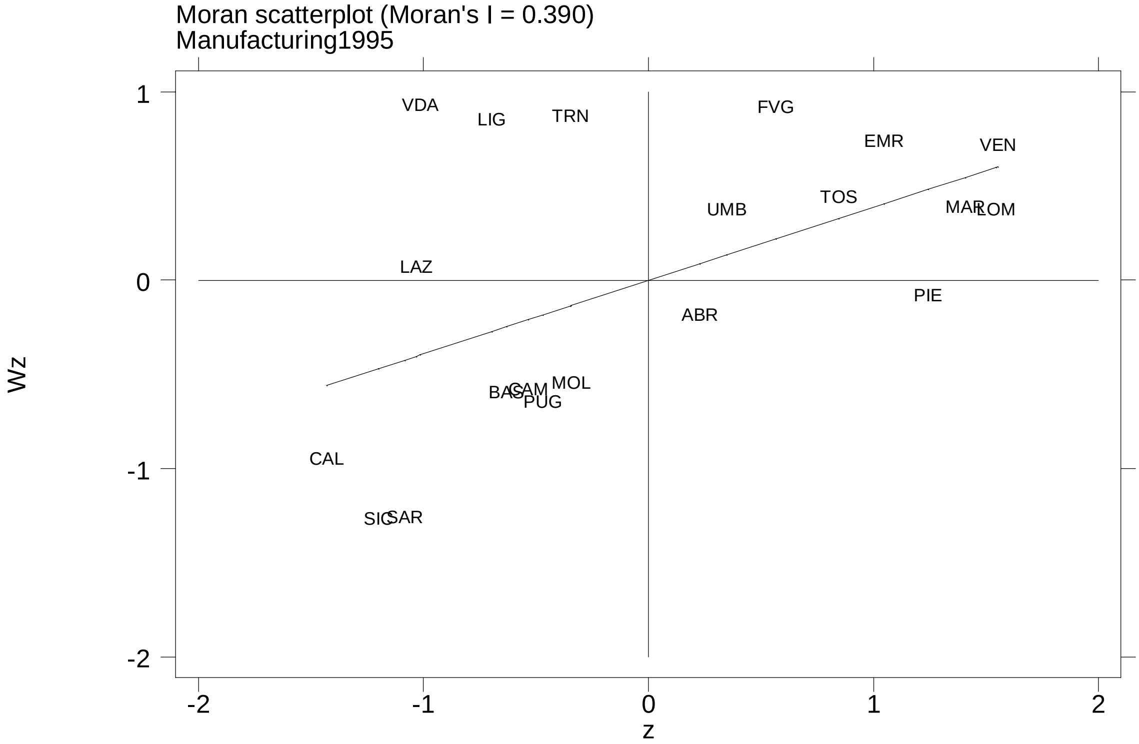

Fig. 23: *Moran scatter plot for Manufacturing Balassa Index 1995*

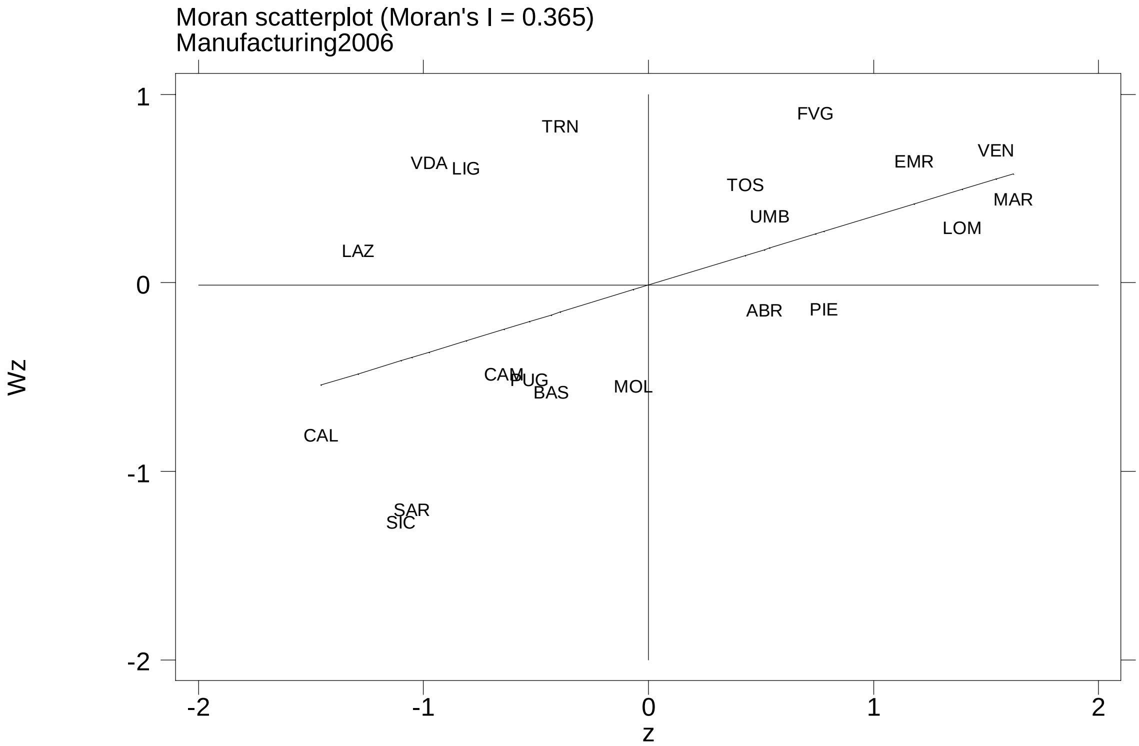

Fig. 24: *Moran scatter plot for Manufacturing Balassa Index 2006*

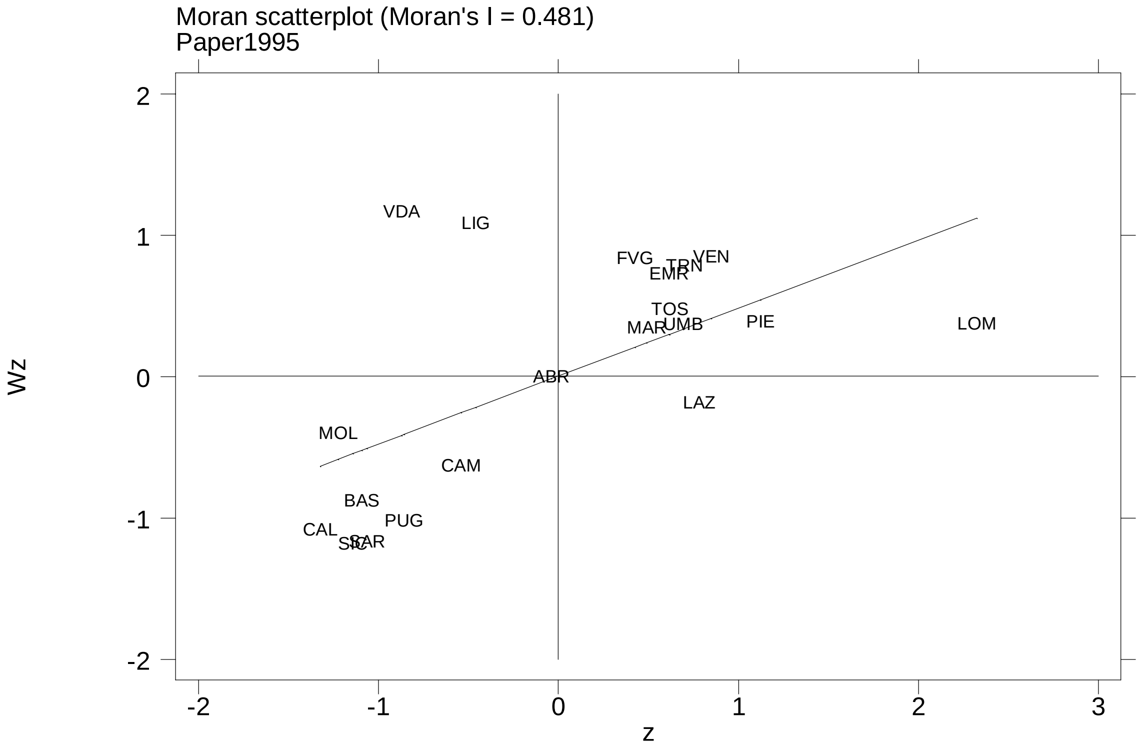

Fig. 25: *Moran scatter plot for Paper Balassa Index 1995*

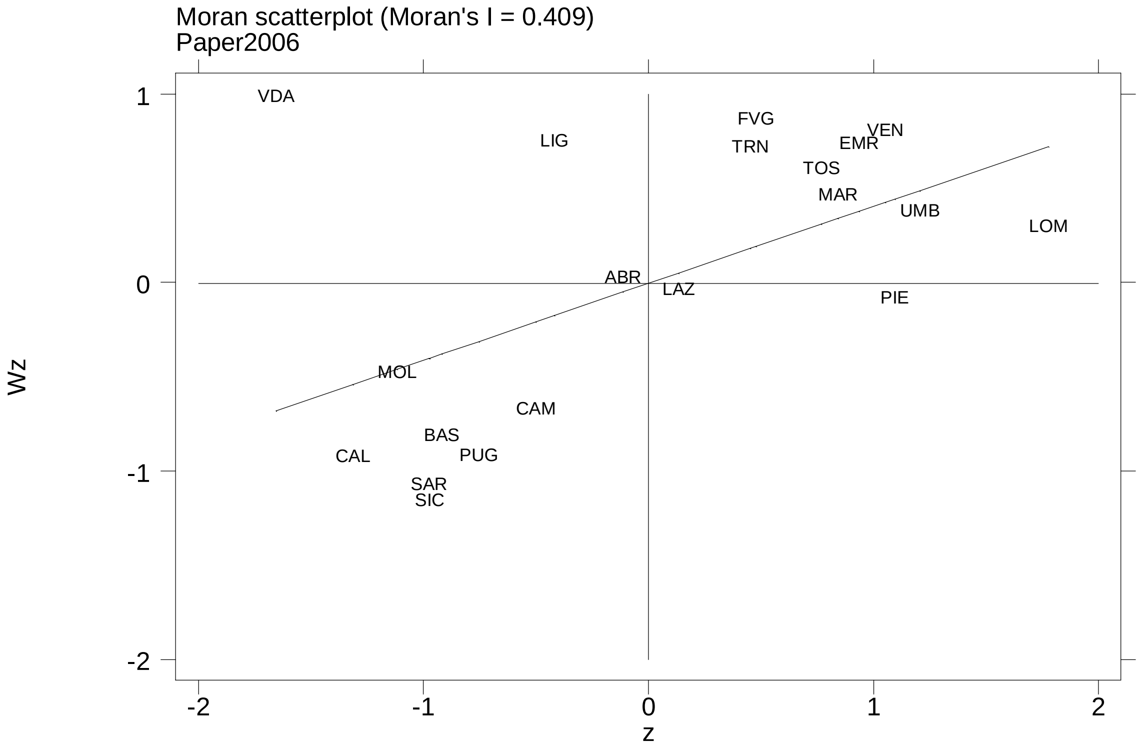

Fig. 26: *Moran scatter plot for Paper Balassa Index 2006*

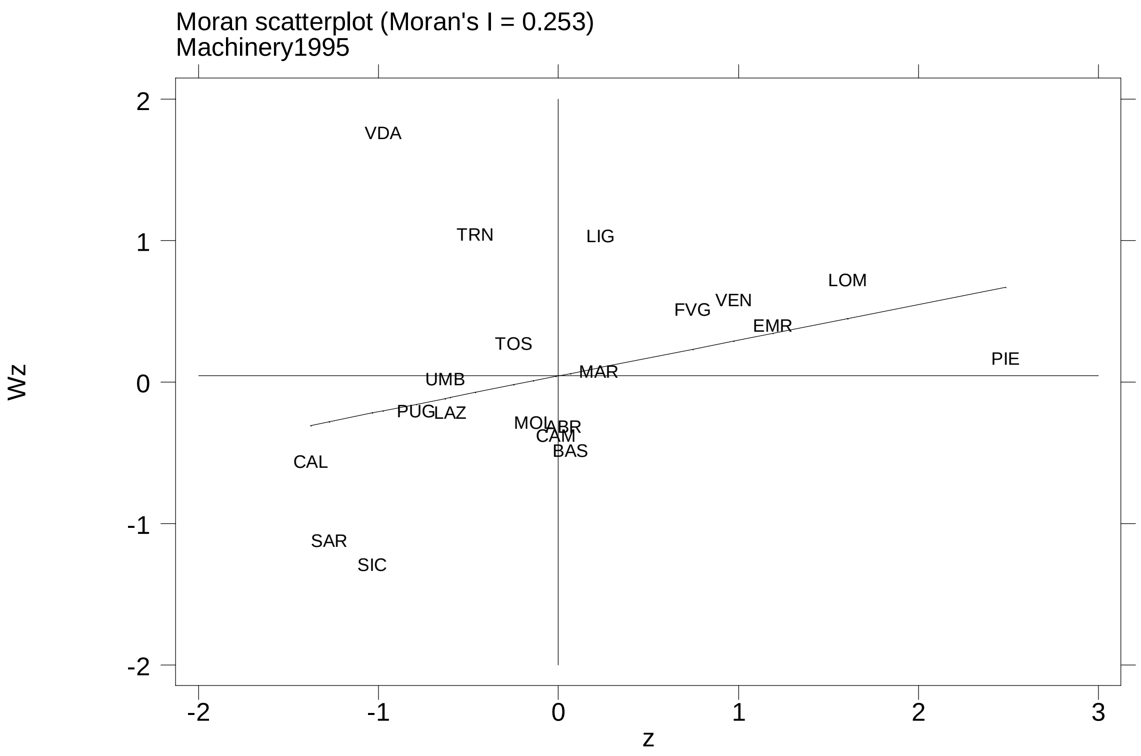

Fig. 27: *Moran scatter plot for Machinery Balassa Index 1995*

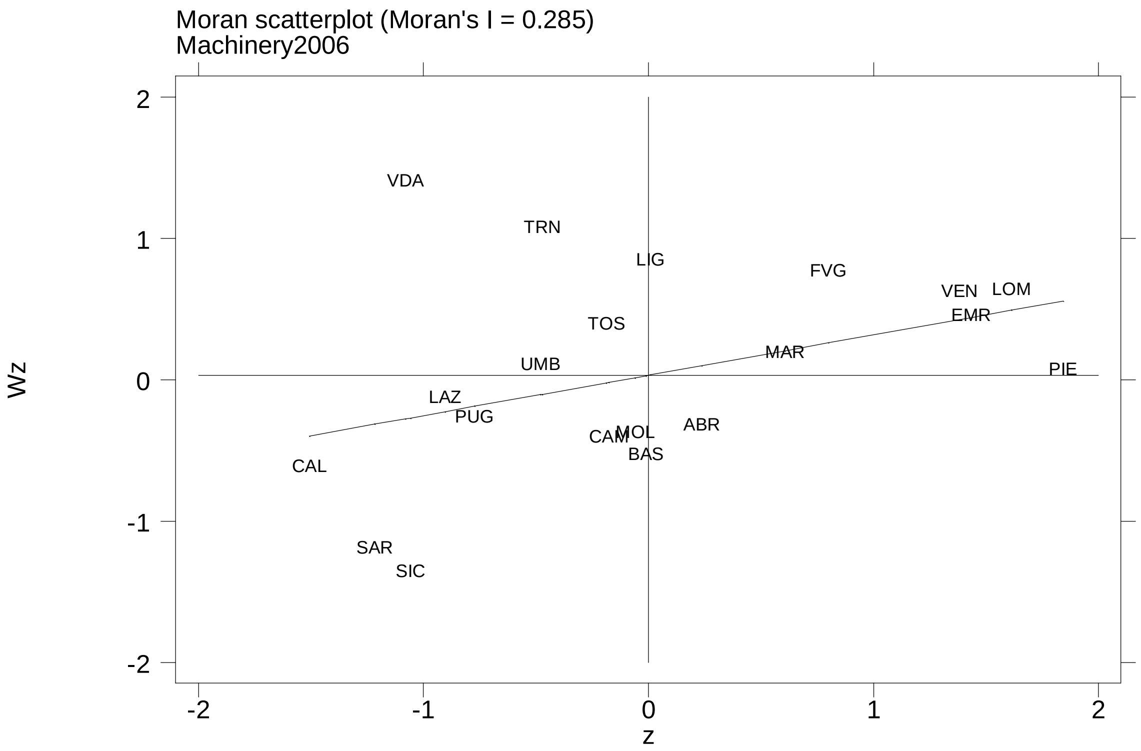

Fig. 28: *Moran scatter plot for Machinery Balassa Index 2006*

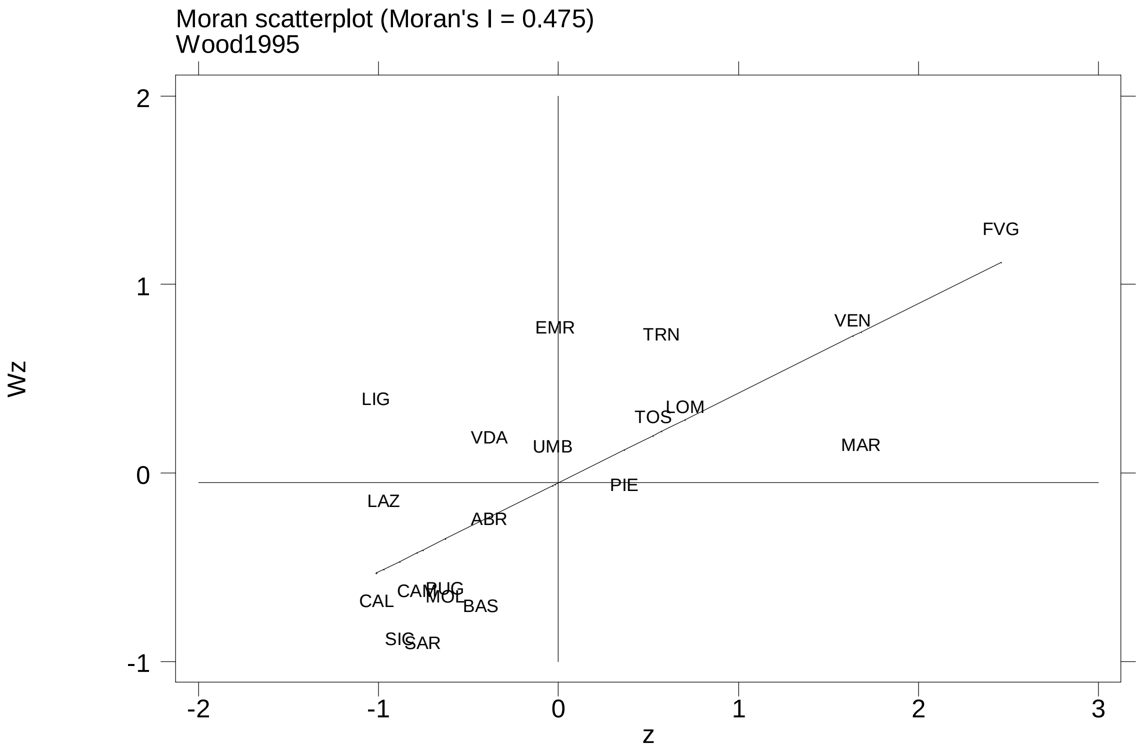

Fig. 29: *Moran scatter plot for Wood Balassa Index 1995*

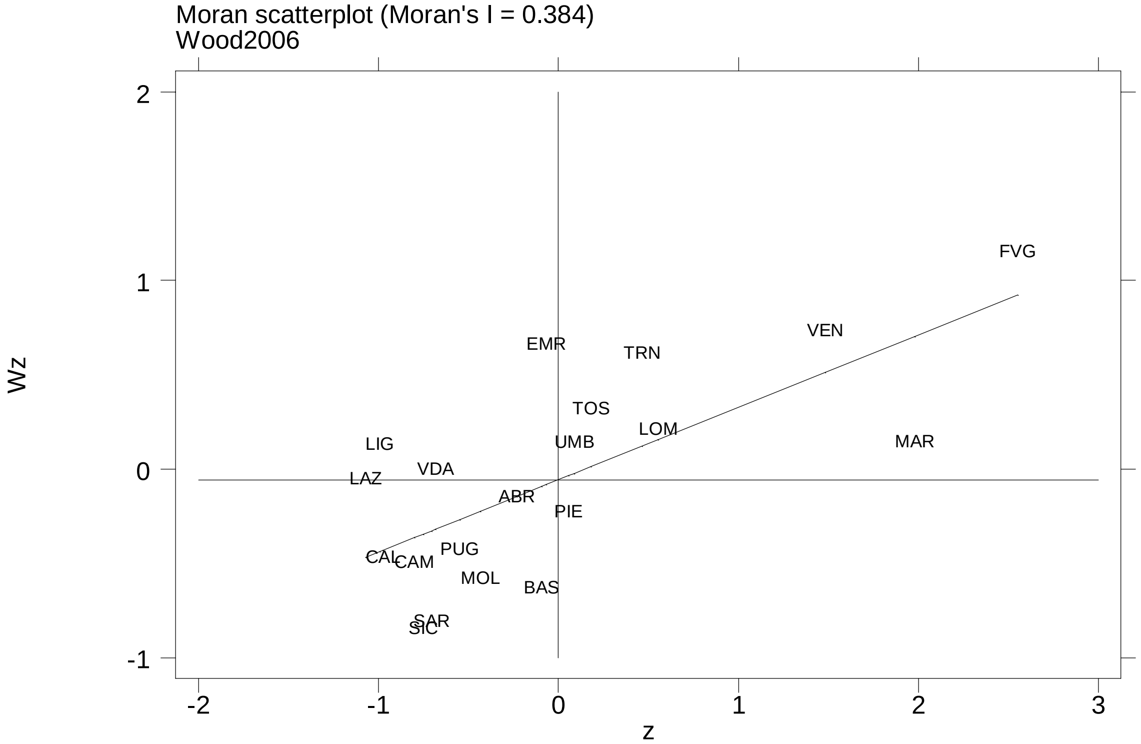

Fig. 30: *Moran scatter plot for Wood Balassa Index 2006*

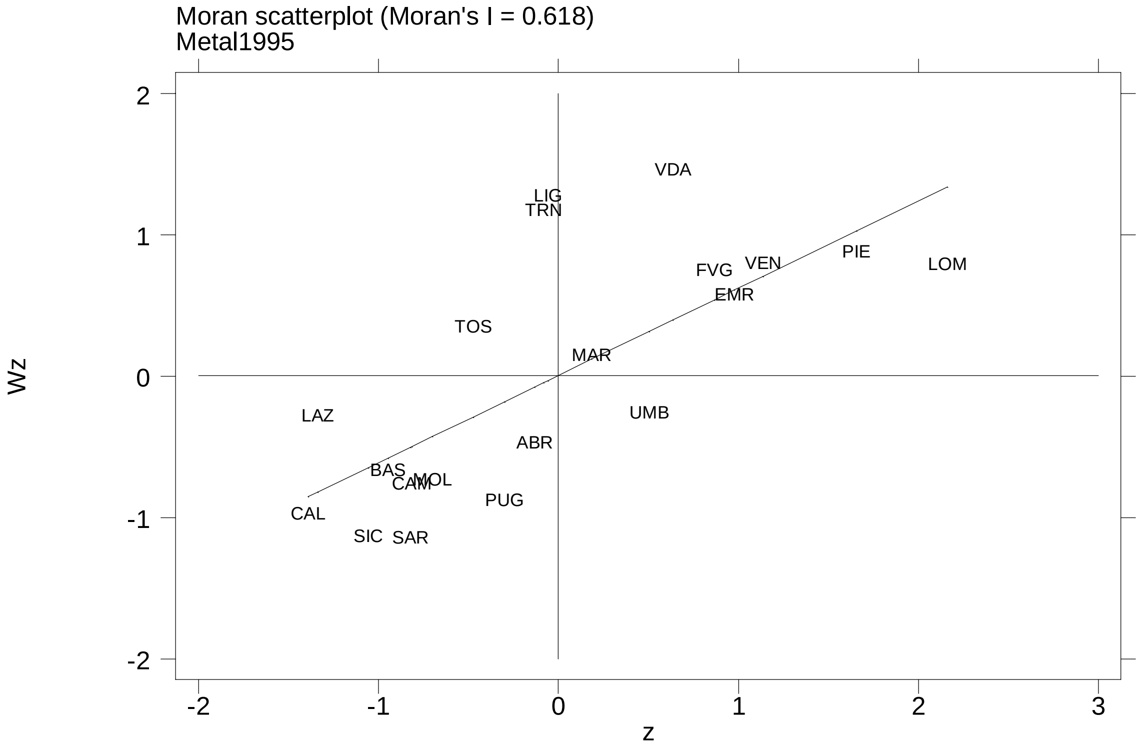

Fig. 31: *Moran scatter plot forMetal Balassa Index 1995*

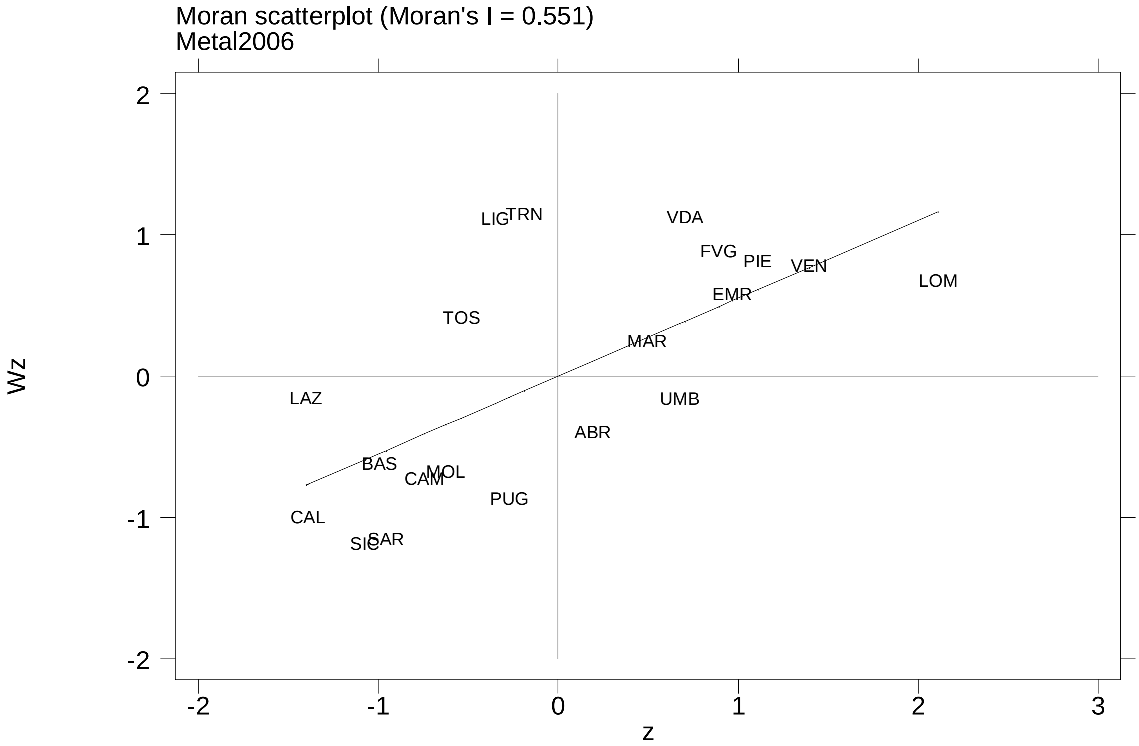

Fig. 32: *Moran scatter plot forMetal Balassa Index 2006*

Table1. *List of sectors and branches and respectve labels*

Sectors and branches	Labels
Agricultural-forestry and fishery products	agriculture
Industry	industry
Strictly industrial activities	strictly industry
Manufacturing industry	manufacturing
Food-beverages-tobacco	food
Textiles and clothing	textile
Tanning industry, leather and similar products	leather
Paper and paper products, press and publishing	paper
Refineries, chemical and pharmaceutical industries	chemical
Products of minerals not metal bearing processing	mineral
Metal and metal goods production	metal
Machinery, mechanical devices, electrical and optical production; means of transports	machinery
Wood, rubber, plastic and other manufacturing industries	wood
Building and construction	construction
Services	services
Wholesale and retail trade; vehicles and motorcycles reparation, personal goods	trade
Hotels and restaurants	tourism
Transports, storage and communications	transport
Monetary and financial intermediation	finance
Real estate, hire, information technology, research, other professional and entrepreneurial activities	real estate

Table 2. *Sectoral specialization indexes descriptive statistics and SMI*

Label		Mean	Std. Dev.	Min	Max	SMI	Label		Mean	Std. Dev.	Min	Max	SMI
Agriculture	overall	1.301	0.751	0.280	3.452	0.20	Metal	overall	0.866	0.402	0.261	1.731	0.18
	between		0.762	0.317	3.205			between		0.410	0.295	1.706	
	within		0.102	1.007	1.729			within		0.035	0.705	0.964	
Industry	overall	0.939	0.235	0.528	1.352	0.32	Machinery	overall	0.820	0.425	0.179	1.945	0.13
	between		0.239	0.562	1.327			between		0.432	0.200	1.799	
	within		0.027	0.849	1.015			within		0.043	0.609	0.966	
Strictly industry	overall	0.890	0.328	0.352	1.441	0.27	Wood	overall	0.957	0.518	0.378	2.377	0.31
	between		0.334	0.383	1.410			between		0.528	0.407	2.243	
	within		0.032	0.791	0.973			within		0.050	0.735	1.143	
Manufacturing	overall	0.883	0.346	0.331	1.464	0.21	Construction	overall	1.106	0.225	0.763	1.787	0.39
	between		0.352	0.366	1.434			between		0.225	0.854	1.662	
	within		0.033	0.778	0.968			within		0.050	0.898	1.231	
Food	overall	1.069	0.287	0.478	1.846	0.34	Services	overall	1.050	0.161	0.769	1.370	0.30
	between		0.290	0.547	1.764			between		0.164	0.777	1.354	
	within		0.048	0.889	1.210			within		0.016	0.991	1.122	
Textile	overall	0.826	0.574	0.100	2.035	0.21	Trade	overall	0.976	0.088	0.722	1.144	0.96
	between		0.585	0.113	1.955			between		0.087	0.776	1.126	
	within		0.053	0.617	1.007			within		0.022	0.915	1.049	
Leather	overall	0.972	1.821	0.000	9.384	0.07	Tourism	overall	1.124	0.487	0.619	2.640	0.27
	between		1.854	0.000	7.908			between		0.496	0.646	2.468	
	within		0.194	0.229	2.448			within		0.048	0.943	1.300	
Paper	overall	0.798	0.387	0.135	1.725	0.29	Transport	overall	0.975	0.209	0.644	1.662	0.87
	between		0.392	0.264	1.592			between		0.212	0.681	1.594	
	within		0.054	0.595	0.942			within		0.025	0.899	1.053	
Chemical	overall	0.739	0.407	0.150	2.202	0.38	Finance	overall	0.909	0.166	0.664	1.400	0.35
	between		0.412	0.237	2.152			between		0.168	0.684	1.354	
	within		0.057	0.556	0.981			within		0.025	0.810	1.002	
Mineral	overall	1.040	0.488	0.131	2.588	0.26	Real estate	overall	0.908	0.178	0.580	1.383	0.37
	between		0.436	0.580	2.123			between		0.180	0.600	1.349	
	within		0.238	0.368	2.825			within		0.028	0.822	1.037	

Table 3. *Moran I statistics for sectoral specialization indexes 1995-2006*

	Agriculture			Industry			Strictly Industry		
Year	**Moran's I**	**Standard Deviation**	**Standardized value**	**Moran's I**	**Standard Deviation**	**Standardized value**	**Moran's I**	**Standard Deviation**	**Standardized value**
1995	0.631	0.136	5.029	0.41	0.139	3.333	0.400	0.139	3.255
1996	0.594	0.136	4.747	0.405	0.139	3.294	0.400	0.139	3.255
1997	0.605	0.136	4.818	0.399	0.139	3.251	0.402	0.139	3.265
1998	0.628	0.136	4.993	0.397	0.139	3.240	0.395	0.139	3.215
1999	0.612	0.135	4.930	0.389	0.139	3.181	0.384	0.139	3.137
2000	0.619	0.134	5.001	0.36	0.139	2.970	0.382	0.139	3.123
2001	0.621	0.133	5.077	0.348	0.139	2.887	0.361	0.139	2.974
2002	0.619	0.130	5.167	0.378	0.139	3.109	0.359	0.139	2.959
2003	0.565	0.129	4.787	0.333	0.139	2.786	0.336	0.139	2.798
2004	0.551	0.129	4.694	0.342	0.138	2.854	0.349	0.139	2.885
2005	0.528	0.128	4.531	0.365	0.138	3.032	0.359	0.139	2.964
2006	0.531	0.127	4.590	0.394	0.138	3.236	0.373	0.139	3.061

All statistics are significant at p=0.0001
Expected value for Moran's I statistics is constant for each year (E(I)=-0.053

Table 3. (*continue*)

	Manufacturing			Paper			Metal		
Year	**Moran's I**	**Standard Deviation**	**Standardized value**	**Moran's I**	**Standard Deviation**	**Standardized value**	**Moran's I**	**Standard Deviation**	**Standardized value**
1995	0.390	0.139	3.178	0.481	0.136	3.923	0.618	0.136	4.922
1996	0.391	0.139	3.187	0.486	0.137	3.942	0.610	0.137	4.849
1997	0.393	0.139	3.200	0.508	0.138	4.076	0.633	0.137	4.985
1998	0.386	0.139	3.153	0.496	0.138	3.980	0.641	0.138	5.027
1999	0.376	0.139	3.080	0.499	0.138	3.987	0.640	0.138	5.028
2000	0.378	0.139	3.088	0.497	0.139	3.969	0.643	0.138	5.046
2001	0.358	0.139	2.950	0.478	0.139	3.828	0.629	0.138	4.953
2002	0.353	0.139	2.911	0.483	0.139	3.853	0.607	0.138	4.790
2003	0.332	0.139	2.762	0.483	0.139	3.858	0.555	0.137	4.426
2004	0.344	0.139	2.850	0.405	0.139	3.304	0.549	0.137	4.381
2005	0.354	0.139	2.923	0.411	0.139	3.345	0.554	0.137	4.423
2006	0.365	0.139	3.004	0.409	0.139	3.325	0.551	0.137	4.397

All statistics are significant at p=0.0001
Expected value for Moran's I statistics is constant for each year (E(I)=-0.05

Table 3. (*continue*)

	Machinery			Wood			Tourism		
Year	**Moran's I**	**Standard Deviation**	**Standardized value**	**Moran's I**	**Standard Deviation**	**Standardized value**	**Moran's I**	**Standard Deviation**	**Standardized value**
1995	0.253	0.133	2.305	0.475	0.133	3.975	0.172	0.123	1.836
1996	0.229	0.133	2.116	0.481	0.133	4.028	0.162	0.122	1.749
1997	0.231	0.133	2.132	0.473	0.132	3.981	0.163	0.124	1.745
1998	0.228	0.133	2.113	0.460	0.132	3.868	0.130	0.122	1.498
1999	0.234	0.134	2.135	0.448	0.134	3.743	0.129	0.121	1.502
2000	0.244	0.134	2.208	0.432	0.133	3.648	0.137	0.120	1.574
2001	0.261	0.134	2.333	0.407	0.134	3.436	0.158	0.123	1.711
2002	0.255	0.135	2.275	0.384	0.133	3.267	0.173	0.124	1.823
2003	0.252	0.136	2.234	0.370	0.133	3.184	0.205	0.126	2.049
2004	0.278	0.137	2.411	0.366	0.133	3.161	0.210	0.125	2.106
2005	0.285	0.137	2.459	0.377	0.132	3.265	0.194	0.126	1.962
2006	0.285	0.137	2.460	0.384	0.130	3.354	0.178	0.125	1.844

Machinery, wood and tourism statistics are significant at p=0.05, p=0.001 and p= 0=0.01, respectively
Expected value for Moran's I statistics is constant for each year (E(I)=-0.05

Table 4. *Robust LMlag and LMerr tests results*

Sectors	robust LMlag	robust LMerr
Agriculture	0.4572	0.7424
Industry	7.5095***	5.6316**
Strictly industry	3.0805*	9.8175***
Manufacturing	1.7573	14.1456***
Mineral	0.0096	0.1413
Textile	0.5057	2.0696
Leather	31.9186***	39.9185***
Metal	0.0652	0.1373
Paper	0.145	1.1563
Wood	106.378***	60.0323***
Machinery	4.7276**	2.6265
Tourism	6.4712**	0.603

***, ** and * denote statistical significance, respectively, at the 1/%, 5% and 10%.

Table 5. *Spatial model estimation results*

	SAR				SEM		
Variables	**Industry**	**Machinery**	**Wood**	**Tourism**	**Strictly industry**	**Manufacturing**	**Leather**
OPEN	0.01***	0.019***	0.025***	0.004**	0.015***	0.015***	0.032***
SE	-1.332***	0.341	-3.638***	1.768***	-1.781***	-2.269***	-16.893***
MP	0.4***	0.495***	-0.725***	-0.529***	0.555***	0.569***	2.14***
POP	-0.011***	-0.017*	-0.034***	-0.079***	-0.014***	-0.004	-0.081
GDP	-0.002***	-0.002*	-0.002*	0.017***	-0.003***	-0.004***	-0.051***
RI	-0.057***	0.07	-0.016	-0.024	-0.043*	-0.104***	-0.324
δ	0.071	-0.118	0.620***	-0.281***			
ρ					-0.296**	-0.921***	-0.756***
LL	349.25	6.722	-13.347	36.205	258.18	197.73	-422.9
R^2adjusted	0.937	0.667	0.765	0.804	0.932	0.913	0.421

*** , ** and * denote statistical significance, respectively, at the 1/%, 5% and 10%.