Industrial Clustering and Sectoral Growth: a Network Dynamics Approach

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ABSTRACT: Cluster analysis has been widely used in an Input-Output framework, with the main objective of uncover the structure of production, in order to better identify which sectors are strongly connected with each other and choose the key sectors of a national or regional economy. There are many empirical studies determining potential clusters from interindustry flows directly, or from their corresponding technical (demand) or market (supply) coefficients, most of them applying multivariate statistical techniques. In this paper we follow a different strategy. Since it is expected that strongly (interindustry) connected sectors share a similar growth and development path, we will try to uncover clusters from sectoral dynamics, by applying a stochastic geometry technique, based on the yearly distances of industry outputs. An application is made, comparing these growth based cluster templates with interindustry based ones, using Portuguese input-output data.

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1. Introduction

Cluster analysis is a useful in industrial and regional economics that became again fashionable particularly after the well known works of Porter (2000; 1998).

Clusters techniques have been widely used in an Input-Output framework with the main objective of uncover the structure of production, in order to better identify which sectors are strongly connected with each other and choose the key sectors of a national or regional economy.

Since the pioneering approaches of Czamansky (1974) and Czamansky and Ablas (1979), many empirical studies have tried to determine the potential clusters from interindustry flows directly, or from their corresponding technical (demand) or market (supply) coefficients.

An interesting example is Hoen (2002) that, after reviewing the traditional *methods of (simple) maximization* and *restricted maximization*, applies a more elaborate *method based on a block diagonal matrix* or the so called *diagonalization method* (using results from Dietzenbacher, 1996).

More recently, Díaz et al (2006) searching for key sectors in an economy use a *fuzzy clustering approach* and Morrillas and Díaz (2008) deal with the *problem of multivariate outliers in industrial clustering*. In a rather different way, Sonis et al (2007), apply the topological principles of the well known Atkin Q-analysis to the identification of clusters of industries in input-output systems.

Another interesting methodology, used in this paper to identify mutually exclusive intersectoral (static) clusters, is the multivariate statistical technique (factor analysis) proposed by Feser and Bergman (2000) and improved in Kelton et al (2008). This technique, based on a principal component analysis extracted from a matrix of 'maximum correlation coefficients' between each pair of (input-output) sectors, is briefly described in section 2.

But our strategy to find sectoral clusters and understand its economic importance is broader in scope. One important issue for the input-output approach to cluster analysis is the connection – if any - between the static network of relationships among agents/sectors and the dynamic behavior of those agents/sectors.

Should we expect that the sectors that compose a cluster as a static entity show similar or at least connected growth paths along a given period of time? Putting it in another way, do static clusters originate dynamic clusters? At first sight the answer is "yes". However there are many reasons that can be given to show that this is not necessarily so.

The main purpose of the paper is to test for the Portuguese economy the hypothesis that sectors that are connected in a static cluster do form a dynamic cluster. For that purpose, after identifying the static clusters with the factor analysis described in section 2, we use for the first time in sectoral input-output studies a stochastic geometry approach to identify what may be called dynamical clusters of sectors (section 3). The description of the industry sectors as a cloud of points in a low-dimensional space suggests evidence for sectoral dynamics and provides a graphic description of the ensemble. Moreover, from the geometrical representation of the economic space of sectors we are able to obtain a topological description of a network of industrial sectors, is such a way that, the structure of the market itself displays patterns of behavior, which defines the collective dynamics.

And finally, in section 4 the two kinds of industry clusters are compared and some concluding remarks are made.

2. Intersectoral (static) clustering

2.1 Methodology

There are several techniques to arrange combinations of sectors using input-output tables. Most of them are based in the interindustry (domestic) flows or in their corresponding technical (intermediate consumptions) and supply (intermediate sales) coefficients (Hoen, 2002).

This paper follows the factor-analysis technique, proposed by Feser and Bergman (2000) and recently improved in Kelton et al (2008). For each pair of sectors, *k* and *l*, there are always four potential relationships: i) *k* buys directly or indirectly from *l*; ii) *k* sells directly or indirectly to *l*; iii) *k* and *l* have similar purchase patterns from other sectors; iv) *k* and *l* have similar sales patterns to other sectors.

Let z_{ij} be the value of the intermediate sales of sector *i* to sector *j*, q_i the value of total intermediate purchases of sector *i* and s_i the corresponding total intermediate sales value. The intersectoral relationships can be quantified by mean of the following four coefficients:

$$x_{ij} = \frac{z_{ij}}{q_j}, x_{ji} = \frac{z_{ji}}{q_i}, y_{ij} = \frac{z_{ij}}{s_i}, y_{ji} = \frac{z_{ji}}{s_j}$$

x_{ij}, x_{ji} represent ***relative purchasing links*** (a large value of x_{ij} indicating that sector *j* depends on sector *i* as a source for a large proportion of its total intermediate inputs).

y_{ij}, y_{ji} represent ***relative sales links*** (a large value of y_{ij} suggesting that sector *i* depends on sector *j* as a market for a large proportion of its total intermediate good sales).

Let x_l be the vector of all the relative purchasing links of sector *l* and y_k the vector of all the relative sales links of sector *k*. The similarities in interindustry structure between sectors k and l can be revealed in a correlation analysis, using the following correlation coefficients:

$r(x_k \cdot x_l)$ - measuring the degree to which sectors *k* and *l* have similar input purchasing patterns

$r(y_k \cdot y_l)$ - measuring the degree to which sectors *k* and *l* have similar selling patterns

$r(x_k \cdot y_l)$ - measuring the degree to which the buying pattern of sector *k* is similar to the selling pattern of sector *l*

$r(y_k \cdot x_l)$ - measuring the degree to which the buying pattern of sector *l* is similar to the selling pattern of sector *k*.

Using an input-output table with *N* sectors and selecting the largest of the four coefficients for each pair of sectors, as the best indicator of similarity between them, yields a *N x N* symmetric matrix of 'maximum correlation coefficients'.

This matrix can than be used in a principal components factor analysis with a promax rotation, in order to better identify the intersectoral (static) clusters.

2.2 Empirical results

In order to identify the inter-sectoral (static) clusters of the Portuguese economy, we use the input-output table of this country for the year 1995 (Dias et al, 2001; Martins, 2004b). As we are interested in the clustering process based on localized interindustry connections, we work with the matrix of domestic flows. We have initially 59 industries, but 4 of them are suppressed because they have null output in the chosen year. A list with the remaining 55 sectors is presented in Table A1.1 of the Appendix 1.

Applying a component principal factor analysis with promax rotation to the 'maximum correlation coefficients' matrix (see sub-section 2.1) gives the list of sectoral clusters presented in Table A2.1 of Appendix 2.

The main result is the identification of a well defined cluster of service industries (and also industries 22-Printed matter and recorded media and 2-Products of forestry, logging and related services).

The second cluster has 7 industries mainly related to metals and fabricated metal products, machinery and equipment and secondary raw materials.

The third cluster relates to construction work and materials, but includes also (unexpectedly?) insurance and pension funding services.

The remaining clusters correspond to: agriculture and food products (4); chemicals, health services and rubber and plastics (5); textiles and wearing, a small cluster of only two industries (6); two energy industries, with a third industry of public services, not easily understandable here (7); mother vehicles and medical and other instruments (8), and, finally a mix of industries difficulty considered a cluster.

About the % of variance explained, there are 2 relatively important eigenvalues (35% of variance explained, the first; 15% the second), and after the third eigenvalue (with 7%) there are a steady decline such that, after the 7th eigenvalue the % of variance explained is below 2%.

For a detailed presentation of these results (SPSS output of this principal component factor analysis) see Appendix 2 (Table A2.2 - Total variance explained; Figure A2.1 - Scree Plot of Eigenvalues by Component Number; Table 4 – Structure Matrix (Promax Rotation).

3. Sectoral growth (dynamic) clustering

In this section, we show how, starting from a stochastic geometry technique, the time evolution of industries (or productive sectors) spontaneously creates a structure, which is conveniently described by a geometrical object.

3.1 Methodology

The stochastic geometry technique is simply stated in the following terms:

Pick a set of sectors and their historical data of outputs over the time interval and compute the yearly difference of the logarithm value of the output (*p*) for each sector (*k*)

$$r(k) = \log(p_t(k)) - \log(p_{t-1}(k)) \tag{1}$$

A normalized vector

$$\vec{\rho}(k) = \frac{\vec{r}(k) - \langle \vec{r}(k) \rangle}{\sqrt{n\left(\langle \overrightarrow{r^2}(k) \rangle - \langle \vec{r}(k) \rangle^2\right)}} \tag{2}$$

is defined, where *n* is the number of components (number of time labels) in the vector $\vec{\rho}(k)$. With this vector one defines the distance between the sectors *k* and *l* by the Euclidian distance of the normalized vectors.

$$d_{ij} = \sqrt{2(1 - C_{ij})} = \left\| \vec{\rho}(k) - \vec{\rho}(l) \right\| \tag{3}$$

with C_{ij} being the correlation coefficient of $r(i)$, $r(j)$.

The fact that d_{ij} is a properly defined distance gives a meaning to geometric notions and geometric tools in the study of the sectors. Given that set of distances between points, the question now is reduced to an embedding problem: one asks, what is the smallest manifold that contains the set? If the proportion of systematic information present in correlations between sectors is small, then the corresponding manifold will be a low-dimensional entity. The following stochastic geometry technique was used for this purpose.

After the distances (d_{ij}) are calculated for the set of N sectors, they are embedded in $\Re^D$, where $D \leq N-1$, with coordinates $\{\vec{x}(k)\}$. The center of mass $\vec{R}$ is computed and coordinates reduced to the center of mass.

$$\vec{R} = \frac{\sum_k \vec{x}(k)}{k} \tag{4}$$

$$\vec{y}(k) = \vec{x}(k) - \vec{R} \tag{5}$$

and the inertial tensor

$$T_{ij} = \sum_k y_i(k) y_j(k) \tag{6}$$

is diagonalized to obtain the set of normalized eigenvectors $\{\lambda_i, \vec{e_i}\}$. The eigenvectors $\vec{e_i}$ define the characteristic directions of the set of sectors. The characteristic directions correspond to the eigenvalues (λ_i) that are clearly different from those obtained from surrogate data. They define a reduced subspace of dimension *d*, which carries the systematic information related to the correlation structure of the productive sectors.

This corresponds to the identification of empirically constructed variables that drive the productive sectors, and, in this framework, the number of surviving eigenvalues is the effective characteristic dimension of this economic space.

As economic spaces can be described as low dimension objects, the geometric analysis is able to provide crucial information about their dynamics. In previous papers, we developed different applications of this technique, namely for the identification of periods of stasis and of mutation of financial markets (Araújo et al., 2007 and 2008; Vilela Mendes et al., 2003).

In the next section we will apply such a dimensional reduction in the identification of clusters of sectors.

3.2 Empirical results

Results were computed using actual data - the set of yearly outputs of 55 sectors with a time window of 12 years - and comparing them to surrogate data that were generated by permuting the output values of each sector randomly in time. As each sector is independently permuted, time correlations among sectors disappear, while the resulting surrogate data preserve the mean and the variance that characterize actual data.

It was empirically found that the set of industrial sectors has only four effective dimensions, as the plot in Fig.1 shows.

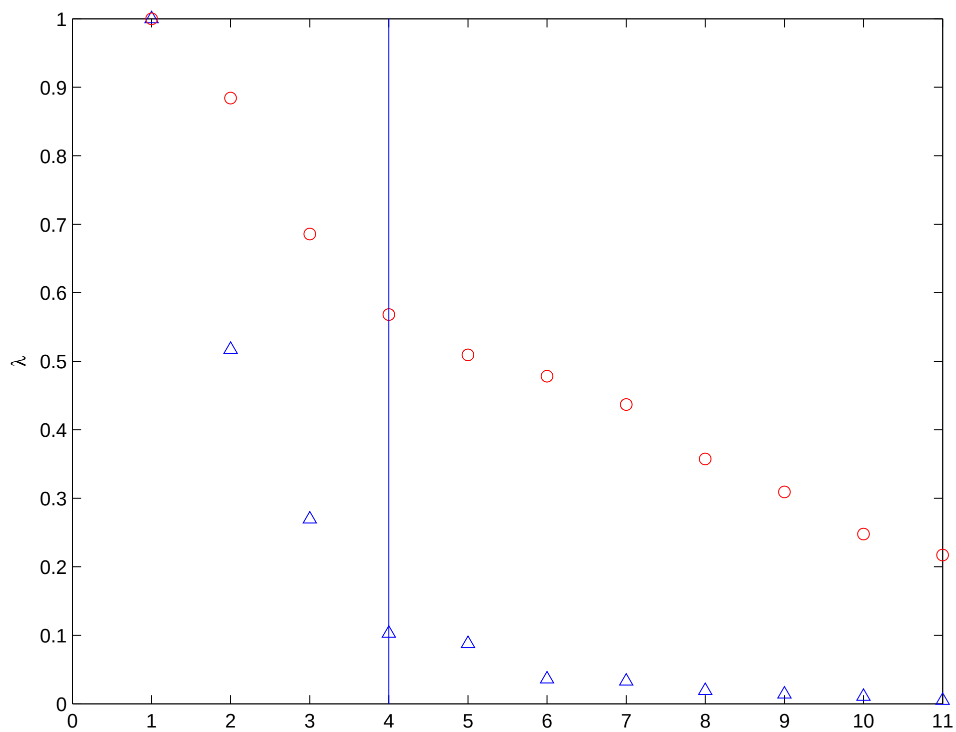

Figure 1: Comparing the decay of the eigenvalues obtained form actual data (∆) and from time permuted data (o)

The four-dimensional space defines the reduced subspace which carries the systematic information related to the correlation structures of the sectors. The four effective dimensions capture the structure of the deterministic correlations and economic trends that are driving the sectoral dynamics, whereas the remainder of the space may be considered as being generated by random fluctuations.

The application of the stochastic geometry technique earlier described to the set of 55 sectors generated the geometrical manifold presented in Figure 2.

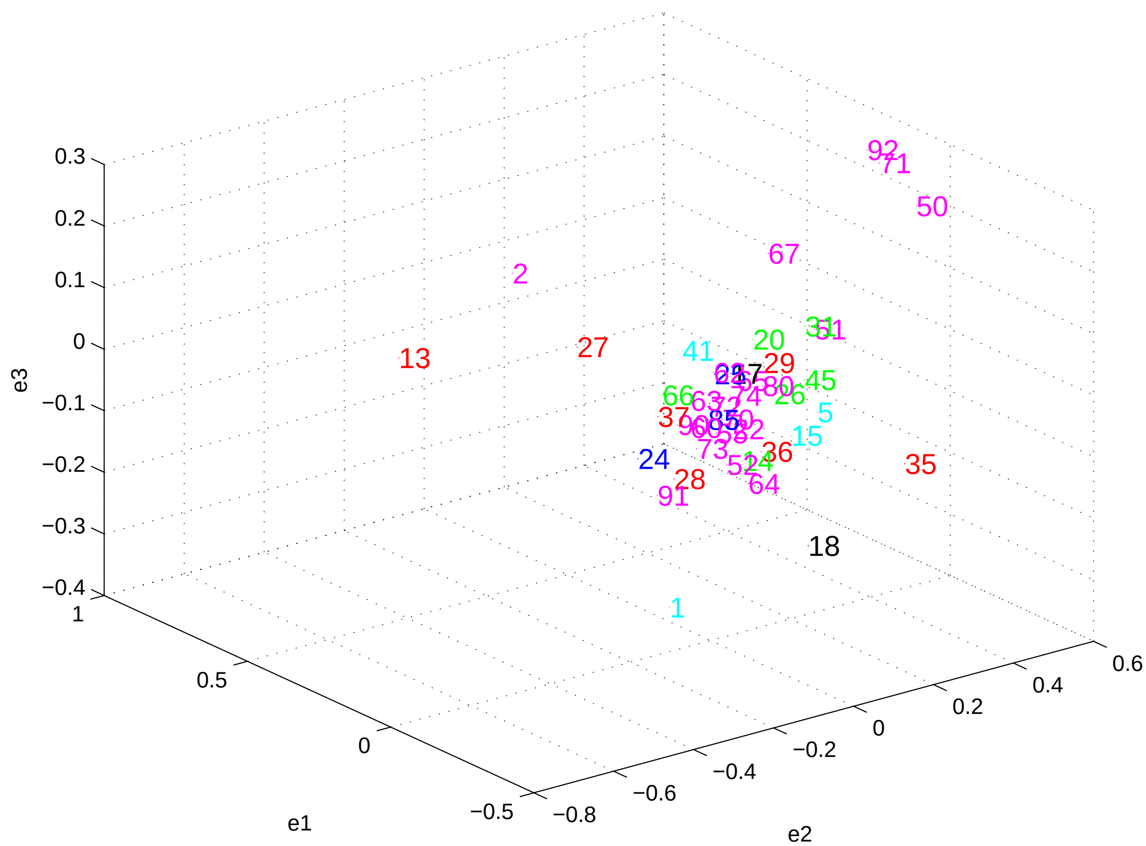

Figure 2: The economic space described along the three dominant directions

In Figure 2, we show the coordinates of each industry, describing the evolution of their dynamics as replicated in the three dominant directions. Different colors identify the corresponding industry clusters (identified in section 2), namely: green (C3), red (C2), magenta (C1), blue (C5), black (C6) and cyan (C4). From the plot in Fig. 2 we observe that some sectors tend to occupy specific locations in the 3-dimensional space. Sectors like the ones numbered 71, 92, 50 and 67 seem to move away from the bulk of the points in the center of the cloud. It is worth noticing that they belong to the same industry cluster (C1 – mainly services).

The previous results suggest that there is a distortion in the dominant directions representing its leading variables. Instead of a close-to-spherical form, the cloud of points in Fig.2, appear to be show prominences and groups of sectors that spread away from the center of the cloud. In order to investigate if such a distortion in the shape of the manifold follows a sectoral pattern, we use a graph representation of the network of sectors, as Fig. 3 shows.

In order to characterize the additional information on the structure of the sectoral space, besides the geometrical approach, we developed a topological representation of the set of productive sectors.

Network of Sectors

From the matrix of distances between sectors (equation 1) computed in the reduced four dimensional space over a time window of 12 years, we apply the hierarchical clustering process to construct the minimal spanning tree (MST) that connects the *N* sectors. Then the Boolean graph B_D^{6} is defined by setting $b(i,j)=1$ if $d^6(i,j)\leq\frac{L_{D^6}}{2}$ and $b(i,j)=0$ otherwise, where L_D^{6} is the smallest threshold distance value that assures connectivity of the whole network in the hierarchical clustering process.

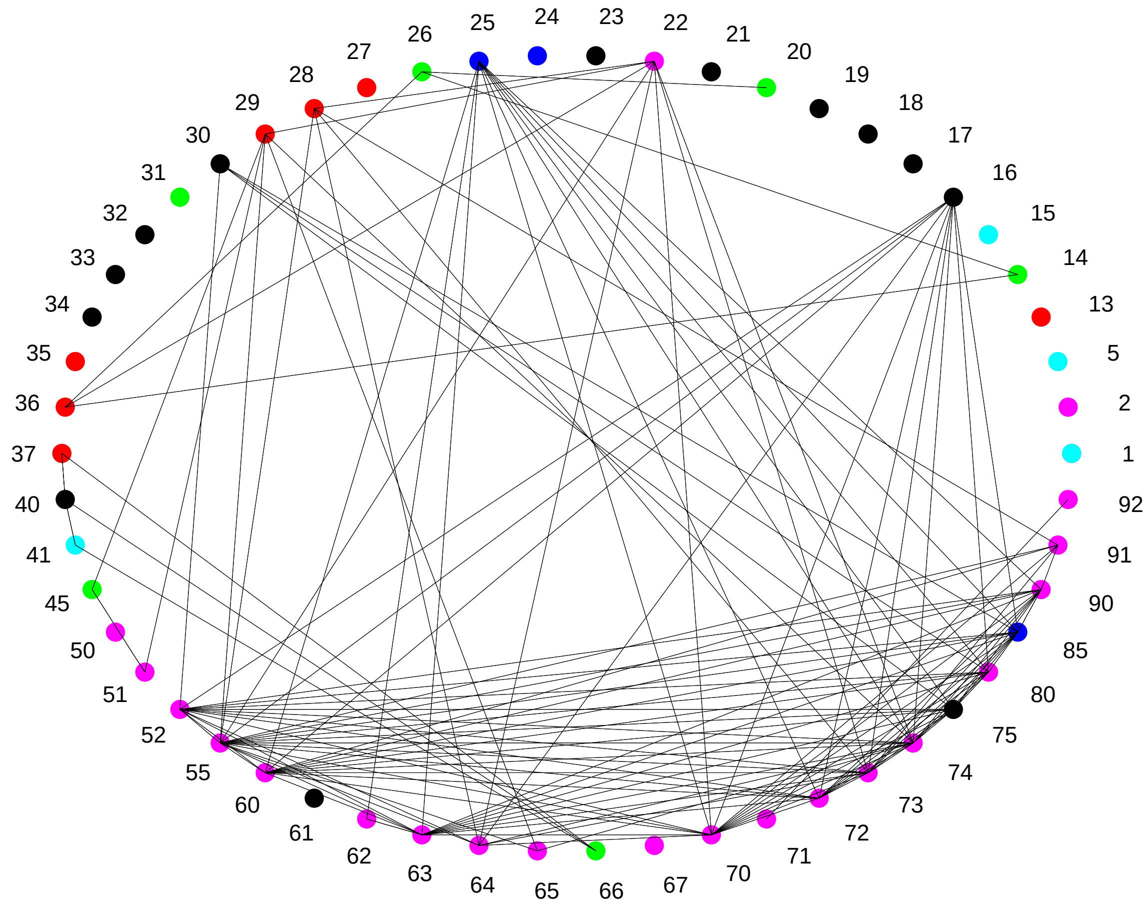

Figure 3: The connected (and generalized) network of sectors

Figure 3 shows the structure of the sectoral pattern, according to the density of relations among sectors. Results show that the amount of highly correlated (short-distant) sectors in the network is not large outside the cluster C1. The network displays a large amount of distances whose values are below the endogenous threshold. This is due to the existence of a relevant set of highly correlated sectors in the first sectoral cluster (C1). Although the values of the overall network distances are low, the existence of highly correlated groups of sectors occupying the prominences in the market distorted shape leads to an increase of the value of the endogenous threshold LD[6].

4. Concluding remarks

In this paper we made a first attempt to identify the industry clusters of the Portuguese economy, using input-output tables of domestic flows from 1995 to 2006.

Starting with the well known methodology proposed by Feser and Bergman (2000), the principal component factor analysis of "maximum correlation coefficients" of intermediate flows, with a promax rotation in order to better interpret the results, we identify a few clusters, namely the most homogeneous one composed by 22 industries, predominantly services. The year chosen as reference for this inter-industry clustering identification is the starting year of the time period covered, 1995.

After that, we try to confirm that, as we might expect, the static clustering structure has implications for the sectoral growth dynamics in the future, that is to say, sectors belonging to the same cluster in 1995 share a common growth performance between 1995 and 2006.

With this purpose in mind, we describe and apply an interesting stochastic geometry technique, based on the yearly distances of industry outputs (or growth rates), and the results appear to confirm our expectation, at least in what concerns the more homogeneous and stronger cluster of services industries.

But for most of the other clusters, inter-sectoral relationships or, more precisely, intermediate based linkages that are the core of input-output analysis, appear not to be strong enough to crucially determine growth dynamics, and other factors should and must be investigated.

Finally, we want to remark that the techniques applied in this study are also useful in other dimensions of input-output analysis, namely regional clusters, value added and employment multipliers and dynamics, sectoral regional or international convergence, to name but a few.

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Appendix 1

Table A1.1 - Industries

Code	Industries
1	Products of agriculture, hunting and related services
2	Products of forestry, logging and related services
5	Fish and other fishing products; services incidental of fishing
13	Metal ores
14	Other mining and quarrying products
15	Food products and beverages
16	Tobacco products
17	Textiles
18	Wearing apparel; furs
19	Leather and leather products
20	Wood and products of wood and cork (except furniture); articles of straw and plaiting materials
21	Pulp, paper and paper products
22	Printed matter and recorded media
23	Coke, refined petroleum products and nuclear fuels
24	Chemicals, chemical products and man-made fibres
25	Rubber and plastic products
26	Other non-metallic mineral products
27	Basic metals
28	Fabricated metal products, except machinery and equipment
29	Machinery and equipment n.e.c.
30	Office machinery and computers
31	Electrical machinery and apparatus n.e.c.
32	Radio, television and communication equipment and apparatus
33	Medical, precision and optical instruments, watches and clocks
34	Motor vehicles, trailers and semi-trailers
35	Other transport equipment
36	Furniture; other manufactured goods n.e.c.
37	Secondary raw materials
40	Electrical energy, gas, steam and hot water
41	Collected and purified water, distribution services of water
45	Construction work
50	Trade, maintenance and repair services of motor vehicles and motorcycles; retail sale of automotive fuel
51	Wholesale trade and commission trade services, except of motor vehicles and motorcycles
52	Retail trade services, ex. of motor vehicles and motorcycles; repair services of personal and household goods
55	Hotel and restaurant services
60	Land transport; transport via pipeline services
61	Water transport services
62	Air transport services
63	Supporting and auxiliary transport services; travel agency services
64	Post and telecommunication services
65	Financial intermediation services, except insurance and pension funding services
66	Insurance and pension funding services, except compulsory social security services
67	Services auxiliary to financial intermediation
70	Real estate services

71	Renting services of machinery and equipment without operator and of personal and household goods
72	Computer and related services
73	Research and development services
74	Other business services
75	Public administration and defence services; compulsory social security services
80	Education services
85	Health and social work services
90	Sewage and refuse disposal services, sanitation and similar services
91	Membership organisation services n.e.c.
92	Recreational, cultural and sporting services
93	Other services

Appendix 2

Table A2.1: Inter-sectoral (static) Clusters

Clusters	Cod	Sectores
C1	71	Renting services of machinery and equipment without operator and of personal and household goods
	74	Other business services
	67	Services auxiliary to financial intermediation
	72	Computer and related services
	80	Education services
	92	Recreational, cultural and sporting services
	90	Sewage and refuse disposal services, sanitation and similar services
	91	Membership organisation services n.e.c.
	63	Supporting and auxiliary transport services; travel agency services
	65	Financial intermediation services, except insurance and pension funding services
	52	Retail trade services, except of motor vehicles and motorcycles; repair services of personal and household goods
	73	Research and development services
	22	Printed matter and recorded media
	70	Real estate services
	50	Trade, maintenance and repair services of motor vehicles and motorcycles; retail sale of automotive fuel
	93	Other services
	51	Wholesale trade and commission trade services, except of motor vehicles and motorcycles
	62	Air transport services
	64	Post and telecommunication services
	55	Hotel and restaurant services
	60	Land transport; transport via pipeline services
	02	Products of forestry, logging and related services
C2	27	Basic metals
	37	Secondary raw materials
	35	Other transport equipment
	28	Fabricated metal products, except machinery and equipment
	13	Metal ores
	29	Machinery and equipment n.e.c.
	36	Furniture; other manufactured goods n.e.c.

C3	26	Other non-metallic mineral products
	45	Construction work
	66	Insurance and pension funding services, except compulsory social security services
	14	Other mining and quarrying products
	20	Wood and products of wood and cork (except furniture); articles of straw and plaiting materials
	31	Electrical machinery and apparatus n.e.c.
C4	05	Fish and other fishing products; services incidental of fishing
	15	Food products and beverages
	01	Products of agriculture, hunting and related services
	41	Collected and purified water, distribution services of water
C5	24	Chemicals, chemical products and man-made fibres
	85	Health and social work services
	25	Rubber and plastic products
C6	18	Wearing apparel; furs
	17	Textiles
C7	40	Electrical energy, gas, steam and hot water
	75	Public administration and defence services; compulsory social security services
	23	Coke, refined petroleum products and nuclear fuels
C8	34	Motor vehicles, trailers and semi-trailers
	33	Medical, precision and optical instruments, watches and clocks
C9	30	Office machinery and computers
	21	Pulp, paper and paper products
	16	Tobacco products
	61	Water transport services
	32	Radio, television and communication equipment and apparatus
	19	Leather and leather products

Table A2.2: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	19,367	35,214	35,214	19,367	35,214	35,214	19,002
2	8,727	15,867	51,080	8,727	15,867	51,080	7,448
3	4,097	7,449	58,530	4,097	7,449	58,530	7,486
4	3,473	6,314	64,844	3,473	6,314	64,844	6,512
5	2,914	5,298	70,142	2,914	5,298	70,142	4,196
6	2,205	4,009	74,151	2,205	4,009	74,151	2,829
7	2,153	3,915	78,066	2,153	3,915	78,066	4,424
8	1,678	3,051	81,117	1,678	3,051	81,117	4,168
9	1,350	2,455	83,572	1,350	2,455	83,572	3,076
10	1,150	2,091	85,663	1,150	2,091	85,663	3,693

11	1,040	1,891	87,554	1,040	1,891	87,554	1,802
12	,914	1,662	89,217				
13	,830	1,509	90,726				
14	,777	1,413	92,139				
15	,714	1,299	93,438				
16	,570	1,036	94,474				
17	,480	,873	95,347				
18	,410	,745	96,091				
19	,362	,658	96,750				
20	,287	,523	97,272				
21	,244	,443	97,716				
22	,155	,283	97,998				
23	,152	,276	98,275				
24	,136	,248	98,522				
25	,117	,213	98,736				
26	,094	,170	98,906				
27	,089	,161	99,067				
28	,083	,152	99,219				
29	,069	,125	99,344				
30	,056	,102	99,446				
31	,041	,075	99,521				
32	,040	,073	99,594				
33	,036	,066	99,660				
34	,034	,063	99,722				
35	,023	,042	99,765				
36	,021	,038	99,802				
37	,019	,034	99,836				
38	,015	,028	99,864				
39	,013	,023	99,887				
40	,011	,021	99,907				
41	,009	,016	99,924				
42	,008	,015	99,939				
43	,007	,012	99,951				
44	,005	,010	99,961				

45	,004	,008	99,969				
46	,004	,007	99,976				
47	,004	,007	99,983				
48	,003	,005	99,988				
49	,002	,004	99,992				
50	,002	,003	99,995				
51	,001	,002	99,997				
52	,001	,002	99,999				
53	,000	,001	100,000				
54	1,851E-5	3,366E-5	100,000				
55	-6,428E-17	-1,169E-16	100,000				

Note: Extraction Method: Principal Component Analysis.

Figure A2.1: Sree Plot of Eigenvalues

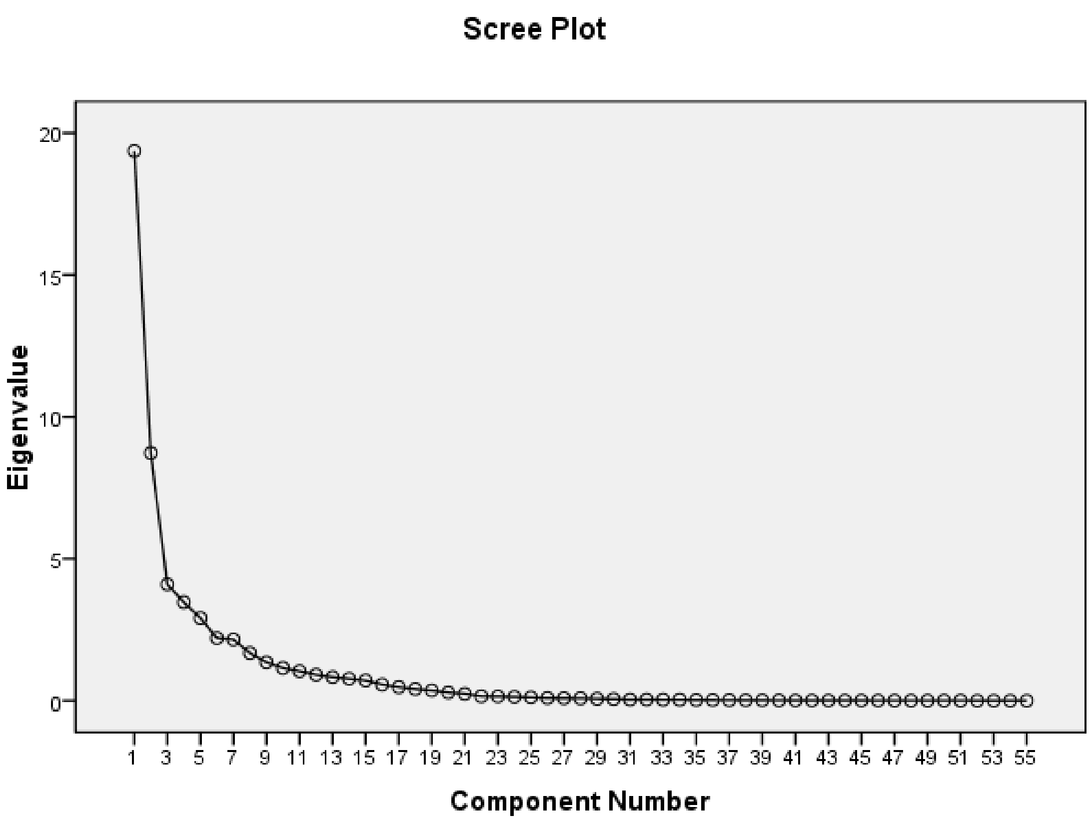

Table A2.3: Structure Matrix (Promax Rotation)

	Component										
	1	2	3	4	5	6	7	8	9	10	11
X71	,970	-,096	,048	,281	,178	,038	,165	,222	,203	,207	-,051
X74	,960	-,208	,025	,305	,345	,058	,210	,104	,232	,172	-,012
X67	,958	-,221	-,002	,211	,263	-,002	,194	,071	,192	,159	,057
X72	,951	-,195	-,023	,192	,268	-,008	,258	,058	,238	,178	,086
X80	,948	-,209	,015	,218	,216	,013	,308	,102	,100	,101	,023
X92	,946	-,226	-,033	,196	,325	-,004	,192	,102	,198	,136	,055
X90	,943	-,176	-,002	,245	,291	,000	,314	,083	,234	,265	,104
X91	,943	-,071	,239	,268	,104	,197	,282	,285	,065	,180	-,186
X63	,943	-,029	,151	,260	,016	,129	,316	,288	,154	,330	-,107
X65	,935	-,166	,161	,309	,205	,187	,291	,099	,107	,137	-,085
X52	,910	-,177	,041	,447	,118	,131	,346	,139	,250	,332	-,019
X73	,881	-,250	-,070	,100	,391	-,136	,234	,117	,091	,026	,150
X22	,878	-,178	-,052	,246	,249	,028	,112	,075	,430	,169	-,020
X70	,869	,030	,470	,206	,165	,018	,196	,231	,051	,226	-,091
X50	,839	-,037	,276	,387	,176	,143	,184	,539	,191	,289	-,074
X93	,808	-,134	,160	,245	,686	,124	,315	,202	,145	,197	-,047
X51	,791	-,011	,314	,682	,146	,253	,270	,359	,123	,245	-,251
X62	,765	,066	,126	,301	-,017	,195	,051	,441	,030	,298	-,337
X64	,752	-,171	,019	,116	-,109	,064	,230	,133	-,137	-,051	-,116
X55	,751	-,098	,129	,748	,094	,155	,036	,270	,159	,184	-,241
X60	,705	,162	,505	,483	,072	,310	,387	,511	,205	,476	-,284
X02	,612	,083	,275	,238	,020	,137	,305	,107	,566	,293	,189
X27	-,293	,952	,457	-,244	-,170	-,098	-,030	,228	-,204	-,064	-,066
X37	-,226	,943	,274	-,191	-,192	-,061	-,048	,221	-,035	-,048	-,087
X35	-,177	,930	,208	-,220	-,169	-,103	-,062	,222	-,188	-,049	-,065
X28	-,063	,859	,746	-,047	-,070	-,001	,063	,331	-,205	,031	-,180
X13	-,037	,852	,411	-,088	-,003	-,002	,394	,185	,018	,240	,056
X29	-,182	,783	,476	-,181	-,122	-,138	,034	,248	-,197	-,165	,032
X36	,155	,773	,602	-,029	-,087	,325	-,021	,492	-,022	,096	-,255

X26	-,012	,484	,935	-,075	,107	,025	,193	,286	-,174	,136	-,140
X45	-,018	,436	,928	-,043	,019	,018	,116	,253	-,226	,102	-,136
X66	,556	,261	,807	,296	,130	,369	,287	,433	,009	,269	-,303
X14	,210	,325	,805	,101	,303	,167	,553	,178	,060	,458	,002
X20	-,059	,313	,792	-,085	-,064	,099	-,023	,157	,155	,038	-,046
X31	-,171	,578	,627	-,254	,087	-,255	,069	,511	-,475	-,269	-,069
X05	,287	-,197	-,041	,907	,014	,068	,216	-,006	,174	,312	-,056
X15	,092	-,263	-,176	,896	-,037	,126	-,038	-,054	,271	,076	,012
X01	,079	-,170	-,038	,889	,062	,181	-,027	,027	,161	,063	-,185
X41	,500	-,101	-,020	,621	,289	,017	,413	,061	,053	,275	,007
X24	,154	-,070	,166	,089	,881	,285	,175	,071	,048	,128	-,103
X85	,694	-,235	,037	,375	,762	,190	,269	,131	,191	,194	-,054
X25	,270	,110	,451	,150	,747	,111	,073	,522	-,147	-,067	-,282
X18	-,047	-,126	-,053	-,017	,069	,857	-,106	-,046	,007	,001	-,202
X17	-,041	-,143	-,008	,067	,333	,843	-,034	-,031	,073	,047	-,154
X40	,130	,020	,067	,045	,091	-,020	,865	-,095	,099	,297	,132
X75	,720	-,065	,138	,373	,054	,021	,761	,093	,077	,341	,090
X23	,052	,161	,624	,090	,242	,055	,672	,084	-,011	,659	,076
X34	-,093	,290	,139	-,055	-,064	-,017	-,146	,740	-,159	-,071	-,107
X33	,258	-,068	-,002	-,129	,516	-,259	,122	,604	-,293	-,246	-,055
X30	-,091	-,139	-,255	-,250	-,128	-,271	-,310	-,410	-,282	-,191	,241
X21	,280	-,116	-,088	,146	,048	,002	,065	-,121	,813	,124	,056
X16	,006	-,278	-,240	,469	-,069	,100	-,181	-,180	,519	,000	,346
X61	,158	-,076	,066	,052	,016	,008	,301	-,027	,052	,827	,047
X32	-,024	-,240	-,194	-,345	,248	-,479	-,085	,285	-,417	-,561	,216
X19	-,099	-,125	-,084	,033	,100	,119	-,155	-,007	-,009	-,076	-,770

Notes: Extraction Method: Principal Component Analysis.

Rotation Method: Promax with Kaiser Normalization.