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ORIGINAL RESEARCH

Cross Sectional and Longitudinal Fuzzy Clustering of the NUTS and Positioning of the Italian Regions with Respect to the Regional Competitiveness Index (RCI) Indicators with *Contiguity* Constraints

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Abstract
In socio-economical clustering often the empirical information is represented by time-varying data generated by indicators observed over time on a set of subnational (regional) units. Usually among these units may exist *contiguity* relations, spatial but not only. In this paper we propose a fuzzy clustering model of multivariate time-varying data, the longitudinal fuzzy C-Medoids clustering with *contiguity* constraints. The temporal aspect is dealt with by using appropriate measures of dissimilarity between time trajectories. The *contiguity* among units is dealt with adding a *contiguity* matrix as a penalization term in the clustering model. The cross sectional fuzzy C-Medoids clustering with *contiguity* constraints is obtained considering one instant of time. The model is applied to the classification of the European NUTS on the basis of the observed dynamics of the Basic, Efficiency and Innovation subindexes of the Regional Competitiveness Index (RCI) 2013 and 2016. The positioning of the Italian regions is analyzed through the values of the medoids of the clusters and shows the peculiarities of the regions with respect to the subindexes either in single times or in the dynamic. Two *contiguity* constraints, one based on the European Western, Southern, Central and Northern geographic areas and one on the level of GDP—taken into account in the computation of the RCI—are also introduced in the models.

Keywords Regional Competitiveness Index (RCI) · European NUTS · Italian regions · Fuzzy clustering · Time trajectories · *Contiguity* constraints

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1 Introduction

In socio-economical clustering often the empirical information is represented by time-varying data generated by Composite Indexes (CIs) observed over time on a set of subnational (regional) units. Usually among these units may exist *contiguity* relations, spatial but not only.

Composite indexes (CIs) which compare country performance are increasingly recognised as a useful tool in policy analysis and public communication. The number of CIs in existence around the world is growing year after year (OECD 2008). Such composite indexes provide simple comparisons of countries that can be used to illustrate complex and sometimes elusive issues in wide-ranging fields, e.g., environment, economy, society or technological development. A composite index is formed when individual indicators are compiled into a single index on the basis of an underlying model. The composite index should ideally measure multi-dimensional concepts which cannot be captured by a single indicator, such as competitiveness, industrialisation, sustainability, single market integration, knowledge-based society. Recently multivariate sets of indicators have been proposed in the framework of the project "Beyond GDP". Born in 2007, the Beyond GDP initiative is about developing indicators that are as clear and appealing as GDP, but more inclusive of environmental and social aspects of progress (Mazziotta and Pareto 2018). Economic indicators such as GDP were never designed to be comprehensive measures of prosperity and well-being.

The OECD Framework for Measuring Well-Being and Progress is based on the recommendations made in 2009 by the Commission on the Measurement of Economic Performance and Social Progress to which the OECD contributed significantly. It also reflects earlier OECD work and various national initiatives in the field. This framework is built around three distinct domains: material conditions, quality of life and sustainability, each with their relevant dimensions.

New measures for assessing specific aspects as Quality of Government have been proposed (Charron et al. 2015).

The classification and positionig of the (geographic) units with respect to the indicators is generally developed using Cluster Analysis. When time information are available, the data are three-way data of type *same units* $\times$ *same variables* $\times$ *time*. Two relevant questions that arise are: *i*) the temporal analysis of single/composite indexes and *ii*) the presence of some relations among units, spatial but not only, as highlighted in Delgado-Marquez and García-Velasco (2018).

The main methodological ways in the literature to aggregate units characterised by similar behaviour across time are the model- feature—and observation based approach. Here we consider the observation-based approach (Caiado et al. 2015; D'Urso 2005; Coppi et al. 2010, and references therein). In the last decade, different fuzzy clustering algorithms have been proposed for both univariate and multivariate time varying-data (see, e.g., Coppi and D'Urso 2002, 2003, 2006; D'Urso et al. 2017a, b).

Similarly, different methods have been suggested in the clustering literature to discover spatial patterns for different kind of spatial units, e.g., urban areas or image pixels. The main challenge these methods overcome is the identification of a suitable algorithm to capture both spatial dependence and spatial heterogeneity. Following the categorisation suggested by Caiado et al. (2015), Fouedjio (2016) classifies clustering of spatial data into four main approaches: non-spatial clustering with geographical coordinates as additional variables; non-spatial clustering based on a spatial dissimilarity measure; spatially constrained clustering; model-based clustering. An example of spatially constrained fuzzy algorithm for urban areas is provided by Di Nola et al. (2000). Examples of applications for image pixels segmentation can be found in Chuang et al. (2006). An approach worth of notice consists in including a spatial penalty term in the objective function of the clustering method, as suggested by Pham (2001). While this proposal has been introduced for solving image segmentation problem, the idea beyond can be easily extended to the clustering of geographical areas (Coppi et al. 2010). In this paper more general *contiguity* relations among units are considered.

In this paper we introduce the Longitudinal Fuzzy C-Medoids Clustering with *contiguity* constraints. It is the Partitioning Around Medoid (PAM) version of the Longitudinal Fuzzy C-Means Clustering with *contiguity* constraints (Coppi et al. 2010). The temporal aspect is dealt with by using appropriate measures of dissimilarity between time trajectories. The *contiguity* among units is dealt with adding a *contiguity* matrix as a penalization term in the clustering model. The novelty with respect to existing Fuzzy C-Medoids Clustering models is the presence of multivariate time-varying data and of the "contiguity" constraints. The Cross Sectional Fuzzy C-Medoids Clustering with *contiguity* constraints is obtained considering one instant of time. Then it is a particular case of the longitudinal version.

The models are applied to the classification of the European NUTS on the basis of the observed dynamics of the Basic, Efficiency and Innovation subindexes of the Regional Competitiveness Index (RCI) 2013 and 2016. The positioning of the Italian regions is deeply analyzed. Two *contiguity* constraints, one based on the European Western, Southern, Central and Northern geographic areas and one on the level of GDP—taken into account in the computation of the RCI—are also introduced in the models. The classifications obtained with and without contraints are compared.

The paper is structured as follows: in Sect. 2 the RCI is presented; in Sect. 3 the Clustering models are introduced; in Sect. 4 the models are applied to the classification of the EU NUTS on the basis of the RCI. Sect. 5 concludes.

2 Regional Competitiveness Index (RCI)

The Regional Competitiveness Index (RCI) (Annoni and Dijkstra 2013, 2017; Annoni et al. 2017) is composed of 11 pillars that describe the different aspects of competitiveness. They are classified into three groups (subindexes): *Basic*, *Efficiency* and *Innovation*.

The Basic group (Table 1) includes five pillars: (1) Institutions; (2) Macroeconomic Stability; (3) Infrastructure; (4) Health; and (5) Basic Education. These represent the key basic drivers of all types of economies (Annoni and Dijkstra 2013; Annoni et al. 2017).

The Innovation group (Table 3) consists of three pillars: (9) Technological Readiness; (10) Business Sophistication; and (11) Innovation.

The complete list of all candidate indicators in RCI 2106 is provided in Tables 1, 2 and 3.

To correct for different range and measurement units, weighted z-scores are adopted with the regions' population sizes as weights. The RCI is obtained in steps: i) as an average of the indicators in each pillar, then as an ii) average of the pillars in each group Basic, Efficiency, Innovation, finally as an iii) average of the subindexes Basic, Efficiency and Innovation. Averages in i), ii) are simple averages, the RCI is obtained as a weighted average of the subindexes Basic, Efficiency and Innovation with weights depending on the stage

Table 1 Indicators of the subindex Basic

Sub-index	Pillar	Indicator
Basic	Institutions	Corruption
Basic	Institutions	Quality and accountability
Basic	Institutions	Impartiality
Basic	Institutions	Country level corruption perception
Basic	Institutions	Regional level corruption perception
Basic	Institutions	Voice and accountability
Basic	Institutions	Political stability
Basic	Institutions	Government effectiveness
Basic	Institutions	Regulatory quality
Basic	Institutions	Rule of law
Basic	Institutions	Control of corruption
Basic	Institutions	Ease of doing business
Basic	Institutions	Property rights
Basic	Institutions	Intellectual property protection
Basic	Institutions	Efficiency of legal framework in settling disputes
Basic	Institutions	Efficiency of legal framework in challenging regulations
Basic	Institutions	Transparency of government policymaking
Basic	Institutions	Business costs of crime and violence
Basic	Institutions	Organized crime
Basic	Institutions	Reliability of police services
Basic	Macroeconomic Stability	Government deficit/surplus
Basic	Macroeconomic Stability	National savings
Basic	Macroeconomic Stability	Government bond yields
Basic	Macroeconomic Stability	Government debt average
Basic	Infrastructure	Motorway potential accessibility
Basic	Infrastructure	Railway potential accessibility
Basic	Infrastructure	Number of passenger flights
Basic	Infrastructure	Intensity of high-speed railways
Basic	Health	Road fatalities
Basic	Health	Healthy life expectancy
Basic	Health	Infant mortality
Basic	Health	Cancer disease death rate
Basic	Health	Heart disease death rate
Basic	Health	Suicide death rate
Basic	Basic Education	Share of low-achieving 15 years olds in reading
Basic	Basic Education	Share of low-achieving 15 years olds in math
Basic	Basic Education	Share of low-achieving 15 years olds in science

of development. The use of simple averages in the first two steps is based on the Principal Component Analysis (PCA), used to check for the internal consistency of each RCI pillar. Each pillar in a composite index describes a particular aspect of the latent phenomenon to be measured. As such aspects are not directly observable, they can only be measured by indicators which are assumed to be related to the aspect they describe and, hence, to

Table 2 Indicators of the subindex Efficiency

Sub-index	Pillar	Indicator
Efficiency	Higher Education	Population 25–64 with higher educational attainment, %
Efficiency	Higher Education	Participation of adults 25–64 in education and training, %
Efficiency	Higher Education	People with at most lower secondary education, % of 18–24
Efficiency	Labor Market Efficiency	Employment rate (excluding agriculture)
Efficiency	Labor Market Efficiency	Long-term unemployment
Efficiency	Labor Market Efficiency	Unemployment rate
Efficiency	Labor Market Efficiency	Labour productivity
Efficiency	Labor Market Efficiency	Gender balance of unemployment
Efficiency	Labor Market Efficiency	Gender balance of employment
Efficiency	Labor Market Efficiency	Female unemployment
Efficiency	Labor Market Efficiency	Share 15–24 not in education, employment, training (NEET)
Efficiency	Market Size	Disposable income per capita
Efficiency	Market Size	Potential market size expressed in GDP (PPS)
Efficiency	Market Size	Potential market size expressed in population

Table 3 Indicators of the subindex Innovation

Sub-index	Pillar	Indicator
Innovation	Technological Readiness	Households with access to broadband
Innovation	Technological Readiness	Individuals buying over Iinternet
Innovation	Technological Readiness	Household access to internet
Innovation	Technological Readiness	Availability of latest technologies
Innovation	Technological Readiness	Firm-level technology absorption
Innovation	Technological Readiness	Technological adoption
Innovation	Technological Readiness	FDI and technology transfer
Innovation	Technological Readiness	Enterprises having purchased online (at least 1%)
Innovation	Technological Readiness	Enterprises having received orders online (at least 1%)
Innovation	Technological Readiness	Enterprises with fixed broadband access
Innovation	Business Sophistication	Employment (K-N sectors)
Innovation	Business Sophistication	GVA (K-N sectors)
Innovation	Business Sophistication	Innovative SMEs collaborating with others
Innovation	Innovation	Total patent applications
Innovation	Innovation	Core creative class employment
Innovation	Innovation	Knowledge workers
Innovation	Innovation	Scientific publications
Innovation	Innovation	Human Resources in Science and Technology (HRST)
Innovation	Innovation	Total intramural R&D expenditure
Innovation	Innovation	Employment in technology and knowledge-intensive average
Innovation	Innovation	High-tech patents
Innovation	Innovation	ICT patents
Innovation	Innovation	Exports in medium-high/high tech manufacturing

Table 4 GDP levels and weights RCI 2016

Stage of development	Basic	Efficiency	Innovation
Stage 1 < 50	35.00	50.00	15.00
Stage 2 50–75	31.25	50.00	18.75
Stage 3 75–90	27.50	50.00	22.50
Stage 4 90–110	23.75	50.00	26.25
Stage 5 > 110	20.00	50.00	30.00

each other.The PCA for each pillar determines the list of artificial variable(s) named *principal components* each containing all the indicators of the pillar with different weights each accounting for as much of the variability in the data as possible in decreasing order. The conditions to be verified to use only one pillar—obtained as a simple average of the indicators measuring that pillar—are that each pillar shows a unique, most relevant PCA accounting for a large amount of variance and that all the indicators contribute to roughly the same extent to the first principal component. To obtain the RCI as a weighted average of the three subindexes EU regions are divided into five development stages based on their average 2012–2014 GDP per head in purchasing power standard (PPS) expressed as an index (EU-28 = 100). The five development stages and the percentage weights of the subindexes are defined for the year 2016 according to Table 4.

2.1 RCI Pillars and Subpillars 2016 and 2013: Main Results

The value of RCI 2016 and of the three subindexes Basic, Efficiency, Innovation for all the NUTS are in Table 5. The value of the RCI in 2013 and 2016, the values of the three subindexes Basic, Efficiency, Innovation in 2013 and 2016 and the values of the eleven Pillars for the Italian regions are described in Table 6.

In Table 7 the RCI 2013 and 2016 in decreasing order for the Italian regions are presented. In Table 8 the detail of the 3 subindexes and the relative absolute and percentual variations 2013–2016 is presented. Italy has 21 NUTS2 regions. They are grouped into 5 NUTS1 levels:

- NORD-OVEST: Piemonte (ITC1), Valle d'Aosta (ITC2), Liguria (ITC3), Lombardia (ITC4)
- NORD-EST: Bolzano (ITH1), Trento (ITH2), Veneto (ITH3), Emilia Romagna (ITH5), Friuli Venezia Giulia (ITH4)
- CENTRO: Toscana (ITI1), Umbria (ITI2), Marche (ITI3), Lazio (ITI4)
- SUD: Abruzzo (ITF1), Molise (ITF2), Campania (ITF3), Puglia (ITF4), Basilicata (ITF5), Calabria (ITF6)
- ISOLE: Sicilia (ITG1), Sardegna (ITG2).

Table 9 lists scores and ranks for each member of the European Union. The final score at country level is computed as regional population weighted average. In 2016 Italy ranks 18th in EU 28 and slips two spots compared to 2013 (16th in 2010): its score has deteriorated from − 0.40 in 2013 to − 0.48 (it was − 0.30 in 2010). Italy is emerging from a long and deep recession but a stagnating economy since the late of 1990s has left the economy

Table 5 Basic (B), Efficiency (E), Innovation (I), GDP level and RCI 2016 for the 256 NUTS

NUTS	B	E	I	GDP	RCI	NUTS	B	E	I	GDP	RCI
UK00	0.604	1.438	1.246	5	1.214	DE25	0.758	0.522	0.708	5	0.625
UKJ1	0.633	1.168	1.466	5	1.150	DEB3	0.753	0.564	0.588	5	0.609
NL31	0.953	1.170	1.245	5	1.149	UKE2	0.387	0.675	0.654	4	0.601
SE11	0.750	1.110	1.444	5	1.138	NL21	0.786	0.476	0.606	4	0.584
UKJ2	0.478	1.111	1.330	5	1.050	DE13	0.692	0.597	0.452	5	0.572
DK01	0.687	0.968	1.337	5	1.022	UKG1	0.348	0.587	0.693	4	0.558
LU00	0.349	0.759	1.741	5	0.972	UKH1	0.306	0.424	1.027	4	0.554
FR10	0.540	1.108	0.961	5	0.950	DE72	0.695	0.535	0.453	4	0.552
DE21	0.737	0.888	1.142	5	0.934	BE22	0.409	0.617	0.551	4	0.550
UKJ3	0.461	0.936	1.149	5	0.905	DK02	0.686	0.494	0.492	3	0.546
NL00	0.726	0.795	1.093	5	0.871	UKF2	0.389	0.562	0.645	4	0.543
DE71	0.839	0.736	1.054	5	0.852	UKD3	0.259	0.576	0.708	4	0.536
DE60	0.689	0.704	1.083	5	0.815	DE00	0.650	0.351	0.738	4	0.523
DE12	0.843	0.763	0.879	5	0.814	DE26	0.791	0.516	0.332	5	0.516
NL41	0.853	0.683	0.995	5	0.811	DK04	0.644	0.440	0.513	5	0.503
UKD6	0.468	0.886	0.909	5	0.809	DE91	0.669	0.248	0.736	5	0.478
NL33	0.835	0.715	0.926	5	0.802	DEA3	0.702	0.456	0.294	4	0.472
BE00	0.498	0.634	1.222	5	0.783	AT00	0.334	0.474	0.555	5	0.470
DE11	0.701	0.787	0.799	5	0.773	DE27	0.746	0.486	0.236	5	0.463
BE21	0.526	0.722	0.902	5	0.737	DE92	0.739	0.315	0.515	5	0.460
NL22	0.766	0.696	0.784	5	0.736	UKE4	0.254	0.461	0.636	4	0.458
DEA2	0.834	0.646	0.758	5	0.717	UKF1	0.293	0.484	0.574	3	0.452
SE22	0.794	0.563	0.884	4	0.702	DE23	0.601	0.387	0.460	5	0.451
UKK1	0.330	0.616	1.081	5	0.698	UKK2	0.180	0.491	0.687	3	0.450
UKJ4	0.517	0.677	0.904	3	0.684	NL11	0.405	0.445	0.464	5	0.442
BE23	0.424	0.771	0.676	4	0.664	DK03	0.689	0.407	0.280	5	0.426
SE23	0.705	0.652	0.651	5	0.663	DEA5	0.734	0.386	0.282	5	0.424

Table 5 (continued)

NUTS	B	E	I	GDP	RCI	NUTS	B	E	I	GDP	RCI
DE14	0.614	0.732	0.576	5	0.662	UKM2	0.092	0.442	0.690	4	0.424
FI1C	0.761	0.487	0.856	5	0.653	FI20	0.720	0.408	0.253	5	0.424
SE12	0.807	0.541	0.697	4	0.645	BE25	0.324	0.549	0.277	5	0.423
NL42	0.809	0.579	0.617	4	0.644	DE24	0.599	0.409	0.322	5	0.421
DEA1	0.794	0.595	0.566	5	0.626	DED2	0.482	0.341	0.467	4	0.407
NUTS	B	E	I	GDP	RCI	NUTS	b	E	I	GDP	RCI
DE50	0.625	0.228	0.555	5	0.405	UKG3	0.322	0.092	0.611	3	0.272
DE73	0.714	0.320	0.313	5	0.397	AT34	0.369	0.263	0.217	5	0.270
DED5	0.569	0.289	0.416	4	0.389	AT22	0.220	0.279	0.285	5	0.269
FR71	0.205	0.465	0.404	4	0.387	DEB2	0.540	0.190	0.146	4	0.262
DK05	0.586	0.293	0.385	4	0.386	CZ00	− 0.101	0.268	0.477	5	0.257
NL13	0.604	0.278	0.388	4	0.384	UKF3	0.169	0.294	0.263	3	0.253
DEA4	0.654	0.340	0.257	5	0.378	AT31	0.288	0.289	0.168	5	0.252
NL34	0.607	0.350	0.222	4	0.377	DE94	0.558	0.190	0.092	5	0.234
FI19	0.655	0.250	0.366	4	0.377	AT32	0.291	0.220	0.215	5	0.233
DEB1	0.721	0.351	0.100	4	0.373	FR42	0.286	0.264	0.120	4	0.232
UKD7	0.198	0.365	0.592	3	0.370	FR52	− 0.093	0.424	0.198	3	0.231
UKG2	0.313	0.404	0.355	3	0.368	IE02	0.084	0.013	0.651	5	0.218
DEF0	0.538	0.244	0.432	4	0.363	UKD1	0.173	0.197	0.258	4	0.208
UKL2	0.151	0.337	0.585	4	0.358	SE31	0.587	0.143	− 0.045	4	0.199
SE21	0.665	0.349	0.088	4	0.355	UKM3	0.053	0.156	0.365	3	0.174
UKM5	− 0.051	0.385	0.574	5	0.355	SI04	− 0.036	0.160	0.362	4	0.167
SE33	0.434	0.278	0.396	5	0.345	DEE0	0.508	0.010	0.081	3	0.163
NL12	0.544	0.211	0.405	4	0.341	FR51	0.043	0.295	− 0.007	4	0.156
ES30	0.195	0.289	0.521	5	0.340	FR24	0.115	0.253	− 0.020	3	0.154

Table 5 (continued)

NUTS	B	E	I	GDP	RCI	NUTS	b	E	I	GDP	RCI
DE93	0.573	0.253	0.222	3	0.334	FR82	− 0.002	0.178	0.230	4	0.149
UKD4	0.195	0.385	0.381	3	0.332	UKC2	0.097	0.054	0.402	3	0.144
UKE3	0.313	0.303	0.360	3	0.319	ES21	− 0.150	0.323	0.015	5	0.136
FR62	− 0.005	0.406	0.441	4	0.318	AT21	0.235	0.145	0.005	4	0.129
DE22	0.514	0.343	0.116	5	0.309	BE35	0.065	0.097	0.249	3	0.122
UKK4	0.064	0.344	0.524	3	0.308	BE33	0.247	− 0.019	0.209	3	0.105
DEG0	0.485	0.281	0.139	3	0.305	UKM6	− 0.119	0.201	0.083	4	0.094
DEC0	0.620	0.148	0.319	5	0.294	FR61	− 0.006	0.115	0.098	4	0.082
SE32	0.502	0.268	0.150	4	0.293	AT11	0.274	0.038	− 0.097	3	0.073
DED4	0.430	0.240	0.235	3	0.291	UKE1	0.156	− 0.018	0.145	3	0.067
AT33	0.436	0.285	0.176	5	0.283	DE80	0.455	− 0.142	0.046	3	0.065
SK01	− 0.486	0.438	0.514	5	0.276	FR43	0.017	0.074	0.094	3	0.063
FI1D	0.551	0.066	0.428	4	0.276	FR72	− 0.127	0.151	0.085	3	0.060
NUTS	B	E	I	GDP	RCI	NUTS	b	E	I	GDP	RCI
FR41	0.054	0.081	0.008	3	0.057	ITH4	− 0.286	− 0.266	− 0.257	4	− 0.268
UKC1	0.105	− 0.064	0.238	2	0.045	ITC1	− 0.251	− 0.295	− 0.255	4	− 0.274
FR23	− 0.016	0.135	− 0.099	4	0.037	CZ07	− 0.179	− 0.323	− 0.432	2	− 0.298
UKK3	− 0.068	− 0.141	0.465	3	0.015	ES13	− 0.193	− 0.297	− 0.441	3	− 0.301
FR26	0.129	0.060	− 0.254	3	0.008	CZ03	− 0.258	− 0.310	− 0.380	2	− 0.307
UKL1	0.008	− 0.072	0.217	2	0.007	ITC3	− 0.301	− 0.333	− 0.290	4	− 0.314
BE34	0.055	− 0.086	0.077	3	− 0.010	CZ08	− 0.282	− 0.267	− 0.502	2	− 0.315
FR30	0.066	0.005	− 0.141	3	− 0.011	ITH3	− 0.204	− 0.253	− 0.515	5	− 0.322
FR25	− 0.090	0.085	− 0.156	3	− 0.017	PL22	− 0.319	− 0.104	− 0.921	2	− 0.324
PT17	− 0.311	− 0.037	0.276	4	− 0.020	PL21	− 0.258	− 0.216	− 0.850	2	− 0.348
FR81	− 0.026	− 0.055	0.034	3	− 0.027	ITI1	− 0.250	− 0.420	− 0.406	4	− 0.376

Table 5 (continued)

NUTS	B	E	I	GDP	RCI	NUTS	b	E	I	GDP	RCI
EE00	0.378	− 0.272	− 0.093	2	− 0.035	ES24	− 0.056	− 0.564	− 0.416	4	− 0.404
FR22	0.093	− 0.026	− 0.230	3	− 0.039	ES12	− 0.268	− 0.476	− 0.455	3	− 0.414
ITC4	− 0.170	0.045	− 0.117	5	− 0.047	ITI2	− 0.341	− 0.371	− 0.632	3	− 0.421
FR21	0.081	− 0.118	− 0.026	4	− 0.047	ITC2	− 0.276	− 0.396	− 0.629	5	− 0.442
UKN0	− 0.045	− 0.213	0.290	3	− 0.054	PL51	− 0.435	− 0.320	− 0.730	3	− 0.444
FR63	− 0.121	0.019	− 0.143	3	− 0.056	PL63	− 0.348	− 0.360	− 0.849	2	− 0.448
BE32	0.102	− 0.213	0.083	3	− 0.060	ITI3	− 0.355	− 0.448	− 0.590	4	− 0.463
FR53	− 0.056	− 0.095	− 0.155	3	− 0.098	ES11	− 0.306	− 0.531	− 0.567	3	− 0.477
ES22	− 0.138	0.042	− 0.307	5	− 0.098	PL11	− 0.434	− 0.339	− 0.925	2	− 0.478
PL12	− 0.322	0.090	− 0.368	4	− 0.128	FR83	− 0.274	− 0.594	− 0.460	4	− 0.483
CZ06	− 0.165	− 0.147	− 0.093	3	− 0.140	ES23	− 0.161	− 0.584	− 0.608	4	− 0.490
HU10	− 0.759	− 0.080	0.208	4	− 0.166	ES52	− 0.165	− 0.669	− 0.494	3	− 0.491
ES51	0.008	− 0.346	− 0.021	4	− 0.176	ES41	− 0.141	− 0.617	− 0.674	3	− 0.499
ITH2	− 0.159	− 0.094	− 0.330	5	− 0.178	CZ04	− 0.367	− 0.592	− 0.659	2	− 0.535
IE01	0.053	− 0.427	0.032	3	− 0.192	PL41	− 0.337	− 0.461	− 1.081	2	− 0.539
ITI4	− 0.287	− 0.241	− 0.081	5	− 0.202	PT16	− 0.377	− 0.538	− 0.837	2	− 0.544
ITH5	− 0.191	− 0.175	− 0.322	5	− 0.222	LV00	− 0.574	− 0.553	− 0.479	2	− 0.546
SI03	− 0.040	− 0.276	− 0.390	2	− 0.224	EL30	− 1.335	− 0.423	− 0.135	4	− 0.564
CZ05	− 0.113	− 0.274	− 0.321	2	− 0.233	PL33	− 0.428	− 0.457	− 1.272	1	− 0.569
ITH1	− 0.236	− 0.062	− 0.608	5	− 0.261	LT00	− 0.924	− 0.291	− 0.717	2	− 0.569
RO32	− 1.302	0.169	− 0.298	5	− 0.265	SK02	− 0.698	− 0.435	− 0.767	2	− 0.579
NUTS	b	E	I	GDP	RCI	NUTS	b	E	I	GDP	RCI
PL31	− 0.469	− 0.509	− 1.129	1	− 0.588	HU31	− 1.056	− 0.859	− 1.019	1	− 0.952
ITF1	− 0.439	− 0.651	− 0.726	3	− 0.610	HU32	− 0.986	− 0.900	− 1.098	1	− 0.960
PL42	− 0.405	− 0.573	− 1.055	2	− 0.611	ITF4	− 0.498	− 1.303	− 0.936	2	− 0.983

Table 5 (continued)

NUTS	b	E	I	GDP	RCI	NUTS	b	E	I	GDP	RCI
ES53	− 0.244	− 0.848	− 0.524	4	− 0.620	PT20	− 0.576	− 1.388	− 0.896	2	− 1.042
PT15	− 0.476	− 0.694	− 0.684	3	− 0.632	ITF6	− 0.575	− 1.344	− 1.082	2	− 1.055
PL43	− 0.412	− 0.616	− 1.078	2	− 0.639	ES64	− 0.315	− 1.611	− 0.887	2	− 1.070
PT11	− 0.355	− 0.793	− 0.745	2	− 0.647	ITG1	− 0.592	− 1.408	− 1.025	2	− 1.081
PL32	− 0.392	− 0.671	− 1.179	1	− 0.650	ES63	− 0.350	− 1.537	− 1.094	3	− 1.111
PL52	− 0.327	− 0.704	− 1.078	2	− 0.656	BG33	− 1.246	− 0.924	− 1.427	1	− 1.112
HU21	− 0.880	− 0.460	− 0.818	2	− 0.658	RO42	− 1.545	− 0.832	− 1.281	2	− 1.139
HU22	− 0.826	− 0.518	− 0.800	2	− 0.667	RO11	− 1.542	− 0.821	− 1.485	1	− 1.173
BG41	− 1.340	− 0.287	− 0.570	2	− 0.669	EL52	− 1.439	− 1.124	− 0.890	2	− 1.179
ITF2	− 0.530	− 0.657	− 0.885	3	− 0.673	BG42	− 1.323	− 1.002	− 1.556	1	− 1.197
ES62	− 0.183	− 0.975	− 0.710	2	− 0.678	EL42	− 1.498	− 1.083	− 1.330	3	− 1.253
PT18	− 0.429	− 0.734	− 1.008	2	− 0.690	BG32	− 1.400	− 1.087	− 1.548	1	− 1.266
SK03	− 0.830	− 0.615	− 0.657	2	− 0.690	RO12	− 1.478	− 1.040	− 1.554	2	− 1.273
PL61	− 0.417	− 0.668	− 1.208	2	− 0.691	EL61	− 1.452	− 1.242	− 1.115	2	− 1.284
PL34	− 0.389	− 0.762	− 1.170	1	− 0.692	EL54	− 1.509	− 1.207	− 1.139	2	− 1.289
PL62	− 0.426	− 0.742	− 1.195	1	− 0.699	EL41	− 1.471	− 1.283	− 1.040	2	− 1.296
ES42	− 0.073	− 1.144	− 0.820	2	− 0.748	EL43	− 1.466	− 1.320	− 1.061	2	− 1.317
ES70	− 0.262	− 1.047	− 0.737	3	− 0.762	RO21	− 1.575	− 1.023	− 1.741	1	− 1.324
ES61	− 0.218	− 1.233	− 0.617	2	− 0.800	EL53	− 1.485	− 1.237	− 1.301	2	− 1.327
HR04	− 0.945	− 0.756	− 0.684	2	− 0.802	BG34	− 1.461	− 1.157	− 1.629	1	− 1.334
HR03	− 0.947	− 0.761	− 0.709	2	− 0.809	RO31	− 1.493	− 1.125	− 1.709	1	− 1.341
PT30	− 0.519	− 1.021	− 0.752	2	− 0.814	RO41	− 1.555	− 1.064	− 1.794	1	− 1.345
HU33	− 1.027	− 0.653	− 1.010	1	− 0.837	EL62	− 1.435	− 1.370	− 1.228	2	− 1.364
SK04	− 0.943	− 0.811	− 0.777	2	− 0.846	EL63	− 1.621	− 1.405	− 1.069	2	− 1.410
ITF5	− 0.561	− 0.959	− 1.059	2	− 0.853	EL65	− 1.508	− 1.450	− 1.314	2	− 1.443

Table 5 (continued)

NUTS	b	E	I	GDP	RCI	NUTS	b	E	I	GDP	RCI
HU23	− 1.023	− 0.761	− 0.913	1	− 0.875	BG31	− 1.557	− 1.294	− 1.683	1	− 1.445
ITF3	− 0.521	− 1.201	− 0.828	2	− 0.918	EL64	− 1.437	− 1.470	− 1.397	2	− 1.446
ITG2	− 0.619	− 1.128	− 0.865	2	− 0.920	EL51	− 1.569	− 1.510	− 1.307	2	− 1.490
ES43	− 0.273	− 1.330	− 0.920	2	− 0.923	RO22	− 1.658	− 1.308	− 1.729	1	− 1.494

Table 6 RCI 2016 Italy eleven pillars

Region		Year	NUTS	PI	PII	PIII	PVI	PV	PVI	PVII	PVIII	PIX	PX	PXI	Basic	Effi-ciency	Innova-tion	GDP	RCI
Piemonte	143	2016	ITC1	− 1.133	− 0.431	0.168	0.419	− 0.279	− 0.857	− 0.278	0.249	− 0.982	0.212	0.004	− 0.251	− 0.295	− 0.255	4	− 0.274
Valle d'Aosta	144	2016	ITC2	− 0.528	− 0.431	− 0.396	0.254	− 0.279	− 1.175	0.178	− 0.192	− 0.986	− 0.361	− 0.540	− 0.276	− 0.396	− 0.629	5	− 0.442
Liguria	145	2016	ITC3	− 1.222	− 0.431	− 0.142	0.570	− 0.279	− 0.718	− 0.207	− 0.073	− 1.007	0.223	− 0.084	− 0.301	− 0.333	− 0.290	4	− 0.314
Lombardia	146	2016	ITC4	− 1.082	− 0.431	0.370	0.574	− 0.279	− 0.755	0.033	0.857	− 0.834	0.400	0.083	− 0.170	0.045	− 0.117	5	− 0.047
Abruzzo	147	2016	ITF1	− 1.334	− 0.431	− 0.638	0.485	− 0.279	− 0.548	− 0.973	− 0.433	− 1.070	− 0.480	− 0.628	− 0.439	− 0.651	− 0.726	3	− 0.610
Molise	148	2016	ITF2	− 1.595	− 0.431	− 0.677	0.335	− 0.279	− 0.692	− 0.718	− 0.561	− 1.194	− 0.572	− 0.889	− 0.530	− 0.657	− 0.885	3	− 0.673
Campania	149	2016	ITF3	− 1.864	− 0.431	− 0.379	0.345	− 0.279	− 1.320	− 1.954	− 0.328	− 1.312	− 0.377	− 0.795	− 0.521	− 1.201	− 0.828	2	− 0.918
Puglia	150	2016	ITF4	− 1.569	− 0.431	− 0.725	0.515	− 0.279	− 1.245	− 1.956	− 0.709	− 1.302	− 0.447	− 1.059	− 0.498	− 1.303	− 0.936	2	− 0.983
Basilicata	151	2016	ITF5	− 1.488	− 0.431	− 1.000	0.393	− 0.279	− 0.822	− 1.191	− 0.865	− 1.349	− 0.834	− 0.994	− 0.561	− 0.959	− 1.059	2	− 0.853
Calabria	152	2016	ITF6	− 1.606	− 0.431	− 0.920	0.363	− 0.279	− 1.057	− 2.007	− 0.969	− 1.413	− 0.601	− 1.232	− 0.575	− 1.344	− 1.082	2	− 1.055
Sicilia	153	2016	ITG1	− 1.560	− 0.431	− 1.024	0.332	− 0.279	− 1.588	− 1.865	− 0.770	− 1.410	− 0.567	− 1.096	− 0.592	− 1.408	− 1.025	2	− 1.081
Sardegna	154	2016	ITG2	− 1.433	− 0.431	− 1.171	0.220	− 0.279	− 1.392	− 1.044	− 0.949	− 0.922	− 0.510	− 1.163	− 0.619	− 1.128	− 0.865	2	− 0.920
Provincia A. di Bolzano	155	2016	ITH1	− 0.369	− 0.431	− 0.559	0.456	− 0.279	− 0.739	0.677	− 0.126	− 0.734	− 0.570	− 0.521	− 0.236	− 0.062	− 0.608	5	− 0.261
Provincia A. di Trento	156	2016	ITH2	− 0.349	− 0.431	− 0.257	0.522	− 0.279	− 0.407	0.059	0.066	− 0.750	− 0.102	− 0.138	− 0.159	− 0.094	− 0.330	5	− 0.178
Veneto	157	2016	ITH3	− 0.916	− 0.431	0.130	0.478	− 0.279	− 0.668	− 0.337	0.246	− 0.899	− 0.209	− 0.436	− 0.204	− 0.253	− 0.515	5	− 0.322
Friuli-Venezia Giulia	158	2016	ITH4	− 0.658	− 0.431	− 0.353	0.291	− 0.279	− 0.580	− 0.095	− 0.124	− 0.777	0.058	− 0.050	− 0.286	− 0.266	− 0.257	4	− 0.268
Emilia-Romagna	159	2016	ITH5	− 0.929	− 0.431	0.332	0.350	− 0.279	− 0.728	− 0.140	0.344	− 0.809	− 0.144	− 0.012	− 0.191	− 0.175	− 0.322	5	− 0.222
Toscana	160	2016	ITI1	− 1.076	− 0.431	− 0.047	0.581	− 0.279	− 0.828	− 0.347	− 0.086	− 0.914	0.018	− 0.324	− 0.250	− 0.420	− 0.406	4	− 0.376
Umbria	161	2016	ITI2	− 1.057	− 0.431	− 0.462	0.525	− 0.279	− 0.369	− 0.480	− 0.263	− 0.955	− 0.302	− 0.638	− 0.341	− 0.371	− 0.632	3	− 0.421
Marche	162	2016	ITI3	− 1.076	− 0.431	− 0.599	0.611	− 0.279	− 0.605	− 0.450	− 0.290	− 0.894	− 0.393	− 0.483	− 0.355	− 0.448	− 0.590	4	− 0.463
Lazio	163	2016	ITI4	− 1.525	− 0.431	0.437	0.360	− 0.279	− 0.467	− 0.426	0.171	− 0.929	0.591	0.095	− 0.287	− 0.241	− 0.081	5	− 0.202

Table 6 (continued)

Region		Year	NUTS	PI	PII	PIII	PVI	PV	PVI	PVII	PVIII	PIX	PX	PXI	Basic	Efficiency	Innovation	GDP	RCI
Piemonte	143	2013	ITC1	− 0.696	− 0.419	0.278	0.458	− 0.459	− 0.846	− 0.047	0.350	− 1.041	0.379	− 0.077	− 0.168	− 0.181	− 0.247	5	− 0.198
Valle d'Aosta	144	2013	ITC2	− 0.405	− 0.419	− 0.202	0.129	− 0.459	− 1.597	0.597	− 0.020	− 0.969	− 0.454	− 0.699	− 0.271	− 0.340	− 0.707	5	− 0.436
Liguria	145	2013	ITC3	− 0.869	− 0.419	0.015	0.705	− 0.459	− 0.475	0.202	− 0.075	− 1.156	0.653	− 0.154	− 0.205	− 0.116	− 0.219	5	− 0.165
Lombardia	146	2013	ITC4	− 0.939	− 0.419	0.777	0.597	− 0.459	− 0.648	0.124	0.865	− 0.909	0.641	0.010	− 0.089	0.114	− 0.086	5	0.013
Abruzzo	147	2013	ITF1	− 1.040	− 0.419	− 0.635	0.416	− 0.459	− 0.365	− 0.581	− 0.460	− 1.098	− 0.328	− 0.761	− 0.427	− 0.469	− 0.729	3	− 0.516
Molise	148	2013	ITF2	− 1.194	− 0.419	− 0.843	0.445	− 0.459	− 0.552	− 0.782	− 0.440	− 1.279	− 0.403	− 1.103	− 0.494	− 0.591	− 0.928	3	− 0.640
Campania	149	2013	ITF3	− 1.688	− 0.419	− 0.330	0.416	− 0.459	− 0.853	− 1.867	− 0.272	− 1.290	0.112	− 0.580	− 0.496	− 0.997	− 0.586	2	− 0.764
Puglia	150	2013	ITF4	− 1.408	− 0.419	− 0.827	0.521	− 0.459	− 1.078	− 1.627	− 0.714	− 1.446	− 0.006	− 0.918	− 0.518	− 1.140	− 0.790	2	− 0.880
Basilicata	151	2013	ITF5	− 1.205	− 0.419	− 0.890	0.393	− 0.459	− 1.235	− 1.111	− 0.721	− 1.338	− 0.422	− 1.083	− 0.516	− 1.023	− 0.948	2	− 0.850
Calabria	152	2013	ITF6	− 1.621	− 0.419	− 1.051	0.524	− 0.459	− 1.220	− 1.184	− 0.931	− 1.327	− 0.121	− 1.111	− 0.605	− 1.112	− 0.853	2	− 0.905
Sicilia	153	2013	ITG1	− 1.453	− 0.419	− 0.945	0.361	− 0.459	− 1.380	− 1.682	− 0.773	− 1.359	0.013	− 0.898	− 0.583	− 1.278	− 0.748	2	− 0.961
Sardegna	154	2013	ITG2	− 1.066	− 0.419	− 1.164	0.385	− 0.459	− 1.059	− 0.974	− 0.995	− 1.001	− 0.026	− 1.003	− 0.545	− 1.009	− 0.676	3	− 0.807
Provincia A. di Bolzano	155	2013	ITH1	− 0.340	− 0.419	− 0.474	0.547	− 0.459	− 1.273	0.747	− 0.232	− 0.905	− 0.388	− 0.541	− 0.229	− 0.253	− 0.612	5	− 0.356
Provincia A. di Trento	156	2013	ITH2	− 0.445	− 0.419	− 0.340	0.730	− 0.459	− 0.607	0.463	0.011	− 0.879	− 0.011	− 0.140	− 0.187	− 0.044	− 0.343	5	− 0.162
Veneto	157	2013	ITH3	− 0.865	− 0.419	0.145	0.540	− 0.459	− 0.815	0.065	0.307	− 0.996	− 0.007	− 0.385	− 0.212	− 0.147	− 0.463	5	− 0.255
Friuli-Venezia Giulia	158	2013	ITH4	− 0.571	− 0.419	− 0.400	0.500	− 0.459	− 0.571	0.165	− 0.095	− 0.974	0.438	− 0.276	− 0.270	− 0.167	− 0.271	5	− 0.219
Emilia-Romagna	159	2013	ITH5	− 0.837	− 0.419	0.203	0.357	− 0.459	− 0.476	0.302	0.448	− 0.959	0.328	− 0.259	− 0.231	0.091	− 0.297	5	− 0.090
Toscana	160	2013	ITI1	− 0.909	− 0.419	− 0.212	0.607	− 0.459	− 0.611	− 0.069	− 0.020	− 0.944	0.289	− 0.312	− 0.279	− 0.233	− 0.322	5	− 0.269
Umbria	161	2013	ITI2	− 0.727	− 0.419	− 0.399	0.503	− 0.459	− 0.337	− 0.137	− 0.222	− 1.063	0.093	− 0.722	− 0.300	− 0.232	− 0.564	4	− 0.335
Marche	162	2013	ITI3	− 0.827	− 0.419	− 0.733	0.632	− 0.459	− 0.736	− 0.099	− 0.238	− 0.962	− 0.030	− 0.774	− 0.361	− 0.358	− 0.589	4	− 0.419
Lazio	163	2013	ITI4	− 1.208	− 0.419	0.333	0.448	− 0.459	− 0.376	− 0.333	0.229	− 0.979	0.804	0.250	− 0.261	− 0.160	0.025	5	− 0.125

Table 7 RCI 2013 and 2016 for Italian regions (z-scores)

Region	NUTS	RCI 2013	Region	NUTS	RCI 2016
Lombardia	ITC4	0.013	Lombardia	ITC4	– 0.047
Emilia-Romagna	ITH5	– 0.090	Provincia Autonoma di Trento	ITH2	– 0.178
Lazio	ITI4	– 0.125	Lazio	ITI4	– 0.202
Provincia Autonoma di Trento	ITH2	– 0.162	Emilia-Romagna	ITH5	– 0.222
Liguria	ITC3	– 0.165	Provincia Autonoma di Bolzano	ITH1	– 0.261
Piemonte	ITC1	– 0.198	Friuli-Venezia Giulia	ITH4	– 0.268
Friuli-Venezia Giulia	ITH4	– 0.219	Piemonte	ITC1	– 0.274
Veneto	ITH3	– 0.255	Liguria	ITC3	– 0.314
Toscana	ITI1	– 0.269	Veneto	ITH3	– 0.322
Umbria	ITI2	– 0.335	Toscana	ITI1	– 0.376
Provincia Autonoma di Bolzano	ITH1	– 0.356	Umbria	ITI2	– 0.421
Marche	ITI3	– 0.419	Valle d’Aosta/Vallée d’Aoste	ITC2	– 0.442
Valle d’Aosta/Valle d’Aoste	ITC2	– 0.436	Marche	ITI3	– 0.463
Abruzzo	ITF1	– 0.516	Abruzzo	ITF1	– 0.610
Molise	ITF2	– 0.640	Molise	ITF2	– 0.673
Campania	ITF3	– 0.764	Basilicata	ITF5	– 0.853
Sardegna	ITG2	– 0.807	Campania	ITF3	– 0.918
Basilicata	ITF5	– 0.850	Sardegna	ITG2	– 0.920
Puglia	ITF4	– 0.880	Puglia	ITF4	– 0.983
Calabria	ITF6	– 0.905	Calabria	ITF6	– 1.055
Sicilia	ITG1	– 0.961	Sicilia	ITG1	– 1.081

behind in many dimensions of RCI: institutions, human capital and labour market continue to be its weakest areas.

The Italian business environment hinders private investment for a number of reasons, including an inefficient legal framework, high taxation and regulations that disincentives Foreign Direct Investments (WEF 2017). Reforms implemented in recent years have improved population perception of corruption. In particular the New Italian Public Procurement Code strengthens the role of ANAC, the National Anti-bribery and Corruption Authority and updates award criteria to include preference based on the “most economically advantageous tender”. But nevertheless the public sector performance remains poor with a highly inefficient judicial system: the time needed to resolve civil, commercial, administrative and other cases is 395 days for the 1st instance compared to 154 in Romania, 17 in Denmark. The Italian labour market has become more efficient in 2015 with the adoption of the “Jobs Act” which introduced three major novelties to Italy’s employment protection legislation: (1). it allows temporary contracts to be renewed up to 8 times (from 5) within a maximum overall duration of 36 months and abolishes the obligation to express the rationale of the temporary contract; (2). it overhauls Art. 18 of Workers’ Charter, already modified in 2012 by the Fornero reform, which regulates dismissals in firms with more than 15 employees (European Commission 2017); (3). it restricts the use of atypical contracts. But nevertheless worker’s skills are deficient as captured by the OECD Programme for the International Assessment of Adult Competencies (PIAAC OECD 2016: the mean proficiency score of 16–65 year-olds in literacy 250.5 and in numeracy 247.1

Table 8 RCI subindexes Basic, Efficiency Innovation 2013 and 2016 for Italian regions (z-scores) and absolute and percentual variations

Region	NUTS	2013			2016			Absolute variation 2013–2016			Percentual variation 2013–2016		
		Basic	Efficiency	Innovation	Basic	Efficiency	Innovation	Basic	Efficiency	Innovation	Basic	Efficiency	Innovation
Piemonte	ITC1	− 0.17	− 0.18	− 0.25	− 0.25	− 0.30	− 0.26	− 0.08	− 0.11	− 0.01	− 49.84	− 63.20	− 3.56
Valle d'Aosta/Vallée d'Aoste	ITC2	− 0.27	− 0.34	− 0.71	− 0.28	− 0.40	− 0.63	0.00	− 0.06	0.08	− 1.73	− 16.62	11.11
Liguria	ITC3	− 0.21	− 0.12	− 0.22	− 0.30	− 0.33	− 0.29	− 0.10	− 0.22	− 0.07	− 46.36	− 186.33	− 32.20
Lombardia	ITC4	− 0.09	0.11	− 0.09	− 0.17	0.04	− 0.12	− 0.08	− 0.07	− 0.03	− 91.46	− 60.59	− 36.14
Abruzzo	ITF1	− 0.43	− 0.47	− 0.73	− 0.44	− 0.65	− 0.73	− 0.01	− 0.18	0.00	− 2.79	− 38.97	0.45
Molise	ITF2	− 0.49	− 0.59	− 0.93	− 0.53	− 0.66	− 0.88	− 0.04	− 0.07	0.04	− 7.17	− 11.04	4.69
Campania	ITF3	− 0.50	− 1.00	− 0.59	− 0.52	− 1.20	− 0.83	− 0.03	− 0.20	− 0.24	− 5.13	− 20.37	− 41.30
Puglia	ITF4	− 0.52	− 1.14	− 0.79	− 0.50	− 1.30	− 0.94	0.02	− 0.16	− 0.15	3.98	− 14.34	− 18.45
Basilicata	ITF5	− 0.52	− 1.02	− 0.95	− 0.56	− 0.96	− 1.06	− 0.04	0.06	− 0.11	− 8.71	6.19	− 11.74
Calabria	ITF6	− 0.61	− 1.11	− 0.85	− 0.57	− 1.34	− 1.08	0.03	− 0.23	− 0.23	5.05	− 20.94	− 26.81
Sicilia	ITG1	− 0.58	− 1.28	− 0.75	− 0.59	− 1.41	− 1.02	− 0.01	− 0.13	− 0.28	− 1.61	− 10.17	− 36.96
Sardegna	ITG2	− 0.54	− 1.01	− 0.68	− 0.62	− 1.13	− 0.87	− 0.07	− 0.12	− 0.19	− 13.57	− 11.81	− 27.87
Provincia Autonoma di Bolzano	ITH1	− 0.23	− 0.25	− 0.61	− 0.24	− 0.06	− 0.61	− 0.01	0.19	0.00	− 3.15	75.30	0.55
Provincia Autonoma di Trento	ITH2	− 0.19	− 0.04	− 0.34	− 0.16	− 0.09	− 0.33	0.03	− 0.05	0.01	14.92	− 112.60	3.90
Veneto	ITH3	− 0.21	− 0.15	− 0.46	− 0.20	− 0.25	− 0.51	0.01	− 0.11	− 0.05	3.80	− 71.76	− 11.22
Friuli-Venezia Giulia	ITH4	− 0.27	− 0.17	− 0.27	− 0.29	− 0.27	− 0.26	− 0.02	− 0.10	0.01	− 5.92	− 59.67	5.25
Emilia-Romagna	ITH5	− 0.23	0.09	− 0.30	− 0.19	− 0.17	− 0.32	0.04	− 0.27	− 0.03	17.21	− 291.58	− 8.43
Toscana	ITI1	− 0.28	− 0.23	− 0.32	− 0.25	− 0.42	− 0.41	0.03	− 0.19	− 0.08	10.15	− 80.31	− 26.05
Umbria	ITI2	− 0.30	− 0.23	− 0.56	− 0.34	− 0.37	− 0.63	− 0.04	− 0.14	− 0.07	− 13.44	− 59.87	− 11.94
Marche	ITI3	− 0.36	− 0.36	− 0.59	− 0.35	− 0.45	− 0.59	0.01	− 0.09	0.00	1.73	− 25.33	− 0.22
Lazio	ITI4	− 0.26	− 0.16	0.02	− 0.29	− 0.24	− 0.08	− 0.03	− 0.08	− 0.11	− 10.10	− 50.50	− 425.41

Table 9 RCI regional population weighted average, regional minimum and maximum

1	Luxembourg	0.97		
2	Netherlands	0.76	0.34	1.15
3	Sweden	0.68	0.20	1.14
4	Denmark	0.64	0.39	1.02
5	United Kingdom	0.60	0.05	0.54
6	Germany	0.54	0.06	0.93
7	Finland	0.51	0.28	0.90
8	Belgium	0.49	− 0.06	0.78
9	Austria	0.33	0.07	0.47
10	France	0.25	− 1.50	0.95
11	Ireland	0.01	− 0.19	0.22
12	Estonia	− 0.04		
13	Czechia	− 0.16	− 0.53	0.26
14	Slovenia	− 0.22	− 0.22	0.17
15	Spain	− 0.39	− 1.11	0.34
16	Poland	− 0.47	− 0.70	− 0.13
17	Portugal	− 0.47	− 1.04	− 0.02
18	Italy	− 0.48	− 1.08	− 0.05
19	Cyprus	− 0.49		
20	Malta	− 0.50		
21	Hungary	− 0.52	− 0.96	− 0.17
22	Latvia	− 0.55		
23	Lithuania	− 0.57		
24	Slovakia	− 0.59	− 0.85	0.28
25	Croatia	− 0.81	− 0.81	− 0.80
26	Greece	− 1.05	− 1.49	− 0.56
27	Bulgaria	− 1.08	− 1.44	− 0.67
28	Romania	− 1.18	− 1.49	− 0.27

are significantly below the average of the 29 OECD countries participating in the Survey of Adult Skills (PIAAC (267.7 and 263.0 respectively). Beside the ultra-Broadband Plan 2020 with a target of 85% of population covered (OECD 2017), in 2016 the government launched the National Industry 4.0 Plan (ISTAT 2018)[1], the first national industry plan explicitly aiming at modernising the productive structure of the economy by providing a

[1] The key incentives to boost investment include:—Hyper-depreciation scheme (introduced with the budget law of 2017): companies will be allowed to deduct 250—Super-depreciation (introduced in 2016 and enhanced in 2017): companies will be allowed to deduct from their taxable income a sum equal to 140% of the original cost of eligible equipment, machineries, software (if connected to investments in industry 4.0 technologies) and other eligible equipment;—Strengthened R&D tax credits for 2017 by raising the share of internal R&D spending that is deductible from companies' taxable income to 50% (from 25%)—the same as for external R&D spending—and raising the annual tax-credit celling to EUR 20 million (from EUR 5 million); Stronger incentives for investing in start-ups and innovative SMEs by: raising the tax credit to 30% (from 19%) of the invested capital in start-ups and innovative SMEs and raising the maximum eligible investment to EUR 1 million (from EUR 0.5 million); allowing companies to claim a tax credit equivalent to losses of controlled start-ups for the first four years of activity; boosting venture capital dedicated to selected industry 4.0 technologies through co-investment schemes with private sector funds.

range of incentives (for about EUR 13 billion) to boost innovation and skills in new technologies over 2017–2020. The Industry 4.0 Plan also aims at enhancing the supply of skills relating to new technology by: implementing the Digital School National Plan; increasing the number of students (at university and post-secondary vocational and education training courses) and doctoral researchers in technical and scientific subjects; creating competence centres and digital innovation hubs to promote cooperation and exchanges among universities, large companies and SMEs, start-ups, business associations and public sector, aiming at supporting the technological transfer and enhancing technical and managerial skills on new technologies.

The distribution of scores across regions is also shown in Table 9: countries are sorted from largest to smallest in terms of internal dispersion measured by the range of variation i.e. the difference between the highest and the lowest score at regional level. France has the largest regional disparities among the European countries, while Italy among the most advanced members is the only one that exhibits negative scores across all its regions, including its capital region (Lazio ITI4 − 0.202): the maximum score is − 0.047 (Lombardia ITC4), the minimum score is − 1.081 (Sicilia ITG1).

3 Cross Sectional and Longitudinal Fuzzy Clustering with *Contiguity* Constraints

By considering an exploratory approach, we analyze the three-way data array of type *same units* × *same quantitative variables* × *time*. This type of three-way data array is called time data array. A time data array can be algebraically formalized as follows: $\mathbf{X} \equiv \{x_{ijt}, i = 1; \dots, I, j = 1, \dots, J; t = 1, \dots, T\}$ where i $(i = 1, \dots, I)$ indicates the unit, $j(j = 1, \dots, J)$ the variable, and $t(t = 1, \dots, T)$ the time. Then, the generic element of $\mathbf{X}$, x_{ijt}, represents the j-th variable observed on the i-th spatial unit at time t. We can denote $\mathbf{X}$ also in the following way: $\mathbf{X} \equiv \{\mathbf{x}_i, i = 1; \dots, I\}$, where $\mathbf{x}_i = \{x_{i11}, \dots, x_{iJT}\}$. The time data array $\mathbf{X}$ can be represented by a bi-dimensional matrix by combining two of the three indices i, j, t on the rows and assigning the remaining index to the columns. In this paper, we analyse only the case in which the time data array $\mathbf{X}$ is represented in the space of the units $\mathfrak{R}^{J+1}$ (the first J dimensions correspond to the J variables and the last dimension is referred to the time). In this space, each unit i is represented, for each time t, by the vector $\mathbf{x}_{it} = \{x_{i1t}, \dots, x_{iJt}\}$ (D'Urso 2004, 2005).

In order to suitably incorporate *constraints* in the clustering procedure, a squared matrix of order I, the *contiguity* matrix $\mathbf{P}$, is introduced. It might be a spatial matrix of adjacency constraints, in case of spatial relations, or a matrix incorporating other *contiguity* relations among units to be taken into account in the clustering procedure. Notice that the diagonal elements of $\mathbf{P}$ are conventionally set equal to zero in order to allow the algebraic manipulation of $\mathbf{P}$.

3.1 Cross Sectional and Longitudinal Fuzzy C-Medoids Clustering with *Contiguity* Constraints

Fuzzy clustering is an overlapping approach which allows cases to belong to more than one cluster simultaneously as opposed to crisp clustering which results in mutually exclusive clusters (Bezdek 1981). In particular, in crisp clustering "each datum is exactly assigned to only one cluster obtaining exhaustive partitions characterized by nonempty and pairwise disjoint subsets. Such crisp assignment of data to clusters can be inadequate in presence of data points that are almost equally distant from two or more clusters. Such special data points can represent hybrid-type or mixture objects, which are (more or less) equally similar to two or more types. A crisp partition arbitrarily forces the full assignment of such data points to one of the clusters, although they should (almost) equally belong to all of them. Fuzzy clustering relaxes the requirement that data points have to be assigned to one (and only one) cluster. Data points can belong to more than one cluster and even with different degrees of membership to the different clusters. This gradual cluster assignment can reflect cluster structure in a more natural way, especially when clusters overlap. Then, the memberships of data points at the overlapping boundaries can express the ambiguity of the cluster assignment (Kruse et al. 2007)". The principal advantages connected to the fuzzy approach are the following (Hwang et al. 2007): (1) Due to the difficulty of identifying a clear boundary between clusters in real applications, fuzzy clustering appears more attractive than the crisp (non-fuzzy) clustering methods (McBratney and Moore 1985; Wedel and Kamakura 1998). (2) The memberships indicate whether there is a second-best cluster almost as good as the best cluster, a scenario which hard clustering methods cannot uncover (Everitt et al. 2001). (3) The fuzzy clustering is attractive because it is easily compatible with distribution free methods. (4) The fuzzy clustering is computationally efficient (McBratney and Moore 1985; Heiser and Groenen 1997).

There are several real cases in which it is more suitable to identify prototypes belonging to the considered dataset, that synthesize the structural information of each cluster, the so-called medoids. Several clustering techniques based on medoids have been proposed, e.g., the Partitioning Around Medoids (PAM) proposed by Kaufman and Rousseeuw (2005). In a fuzzy framework, Krishnapuram et al. (1999) Krishnapuram et al. (2001) suggested the so-called Fuzzy C-Medoids clustering method. Notice that using the Partitioning Around Medoids (PAM) approach, the prototypes of each cluster, henceforth medoids, are regions actually observed and not "virtual" regions like the "centroids" derived with a fuzzy C-means clustering approach. Overall, having non-fictitious representative regions available makes interpreting the obtained clusters easier, which is often very useful in geographical applications. In fact, "in many clustering problems one is particularly interested in a characterization of the clusters by means of typical or representative objects [regions]. These are objects [regions] that represent the various structural aspects of the set of objects [regions] being investigated. There can be many reasons for searching for representative objects [regions]. Not only can these objects [regions] provide a characterization of the clusters, but they can often be used for further work or research, especially when it is more economical or convenient to use a small set of k objects [regions] instead of the large set one started off with" (Kaufman and Rousseeuw 2009). We observe that PAM-based fuzzy clustering represents a robustification of the fuzzy C-means clustering; however, it provides only a "timid robustification" of the fuzzy C-means clustering, because a single outlier still serves to breakdown the clustering (García-Escudero and Gordaliza 1999). As remarked by García-Escudero et al. García-Escudero et al. (2010) the clustering based on medoids "resists to the presence of 1 outlier in a remote position, but it breaks down when we increase to 3 the number of outliers".

In this section the Longitudinal Fuzzy C-Medoids Clustering model with *Contiguity* constraints (L-FCMd-C) is introduced. It is a Partition Around Medoids (PAM) version of the model suggested by Coppi et al. (2010). The L-FCMd-C model is formalized in the following way:

$$\min : \quad \sum_{i=1}^{I}\sum_{c=1}^{C} u_{ic}^{m}\sum_{t=1}^{T}(w_t d(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{ct}))^2 + \frac{\beta}{2}\sum_{i=1}^{I}\sum_{c=1}^{C} u_{ic}^{m}\sum_{i'=1}^{I}\sum_{c'\in C_c} p_{ii'}u_{i'c'}^{m} \tag{1}$$

$$\sum_{t=1}^{T} w_t = 1,\ w_t \geq 0 \tag{2}$$

$$\sum_{c=1}^{C} u_{ic} = 1,\ u_{ic} \geq 0 \tag{3}$$

where u_{ic} denotes the membership degree of the i-th unit to the c-th cluster; $d(\mathbf{x_{it}}, \tilde{\mathbf{x}}_{\mathbf{ct}})$ is a suitable Euclidean distance between the i-th unit $\mathbf{x}_{it} = \{x_{i1t}, \dots, x_{iJt}\}$ and the medoid of the c-th cluster $\tilde{\mathbf{x}}_{ct} = \{\tilde{x}_{c1t}, \dots, \tilde{x}_{cJt}\}$ at time $t, m > 1$ is a parameter controlling the fuzziness of the partition (for the selection of m, see D'Urso 2015), $\mathbf{P} \equiv \{p_{ii'}, i = 1; \dots, I, i' = 1; \dots, I\}$ is the *contiguity* matrix ($p_{ii'} = 1$ for *contiguous* i, i'; 0 otherwise), w_t is the tuning parameter of the temporal information; $\beta \geq 0$ is the tuning parameter of the spatial information; C is the number of clusters.

The objective function (1) is optimized with respect to the medoids $\tilde{\mathbf{x}}_c (c = 1, \dots C)$, chosen among the n units, the membership degrees u_{ic} and the temporal weights w_t. The medoids corresponding to the optimization solution provide a fuzzy partition via u_{ic}.

The objective function cannot be minimized by means of the alternating optimization algorithm, because the necessary conditions cannot be derived by differentiating it with respect to the medoids. Nonetheless, following heuristic algorithm of Fu (1982) for a crisp version (corresponding to $m = 1, u_{ic} = 1$ or 0) of the objective function, a fuzzy clustering algorithm that minimizes the objective function can be built up (Krishnapuram et al. 2001).

As far as the Euclidean distance $d(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{ct})$ is concerned, two types of dissimilarity measures for multivariate trajectories are used (Coppi and D'Urso 2001, 2006; D'Urso 2004, 2005): the dissimilarity that compares the time trajectories for the different time instants, i.e. $d(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{ct}) = ||\mathbf{x}_{it} - \tilde{\mathbf{x}}_{ct}||,\ t = 1, \dots, T$ and the dissimilarity that considers the variation $\mathbf{v}_{it} = (\mathbf{x}_{it} - \mathbf{x}_{it-1})$ concerning the evolutive features (i.e. the "variational" patterns) of the trajectories measured by means of their absolute variation i.e. $d(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{ct}) = ||\mathbf{v}_{it} - \tilde{\mathbf{v}}_{i't}||,\ t = 2, \dots, T$. Also the percentual variation $\mathbf{vr}_{it} = \frac{(\mathbf{x}_{it} - \mathbf{x}_{it-1})}{\mathbf{x}_{it-1}} 100$ has been considered i.e. $d(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{ct}) = ||\mathbf{vr}_{it} - \tilde{\mathbf{vr}}_{i't}||,\ t = 2, \dots, T$.

If in (1) we consider $T = 1$ we obtain the Cross Sectional Fuzzy C-Medoids Clustering model with *Contiguity* constraints (CS-FCMd-C).

In Fig. 1 an example of Cross Sectional and Longitudinal clustering is shown.

3.2 Some Remarks: Cluster Validity and Contiguity Correlation

The parameters to be fixed in model (1) are the number of clusters C and the spatial parameter β.

A widely used cluster validity criterion for selecting C is the fuzzy extension of the *Silhouette criterion* (Campello and Hruschka 2006).

The Fuzzy Silhouette makes explicit use of the fuzzy partition matrix $\mathbf{U} = \{u_{ik} : i = 1, \dots, I; c = 1, \dots, C\}$. It considers the information on the membership degrees contained in the fuzzy partition matrix $\mathbf{U}$ by stressing importance of units concentrated in the vicinity of the cluster prototypes (high membership) while reducing importance of units lying in overlapping areas (small membership). The Fuzzy Silhouette (*FS*) is defined as follows:

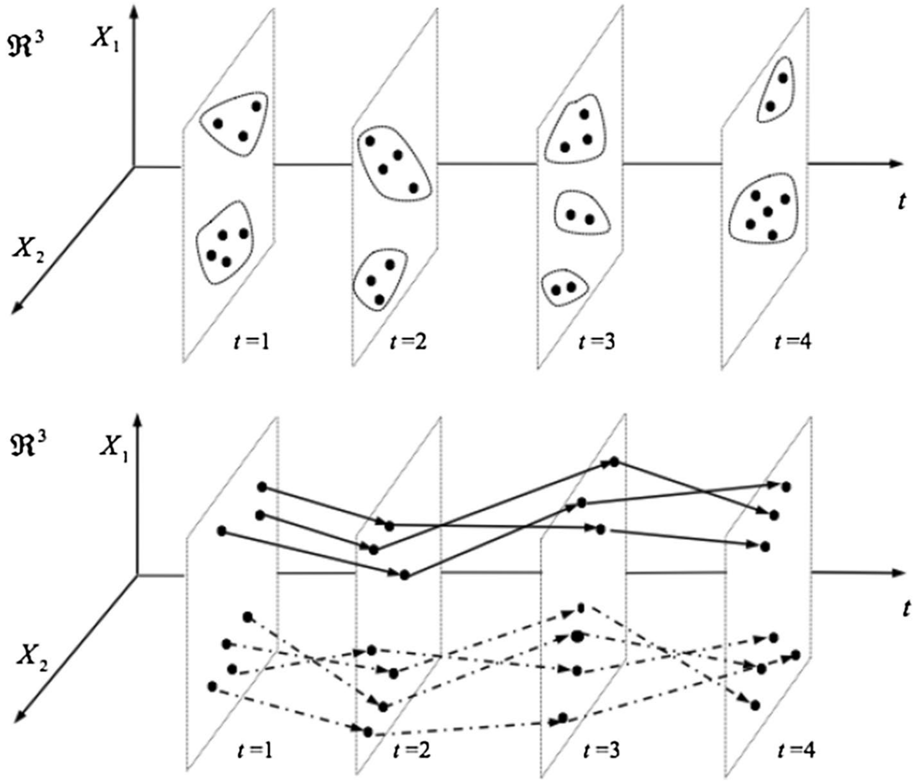

Fig. 1 Example of cross sectional and longitudinal clustering ($I = 7, J = 2, T = 4$) (D'Urso 2005)

$$FS = \frac{\sum_{i=1}^{I}(u_{ic} - u_{ic'})^{\gamma} S_i}{\sum_{i=1}^{I}(u_{ic} - u_{ic'})^{\gamma}} \quad S_i = \frac{(b_i - a_i)}{max\{b_i, a_i\}} \tag{4}$$

where a_i is the average distance between the i-th unit and the units belonging to the cluster $p (p = 1, \dots, C)$ with which i is associated with the highest membership degree; b_i is the minimum (over clusters) average distance of the i-th unit to all units belonging to the cluster q with $q \neq p$, u_{ik} and $u_{ik'}$ are the first and second largest elements of the i-th row of the fuzzy partition matrix, respectively, and $\gamma \geq 0$ is a weighting coefficient. The effect of varying this parameter on the weighting terms in (4) is investigated in Campello and Hruschka (2006).

The selection of the optimal value of β is a complex issue. A possible way to solve it is represented by the following heuristic procedure, assuming C and m have already been chosen. For every specified value of β, the obtained clusters are constructed in such a way that the within cluster dispersion is minimized. However, it would be also desirable that each and every clusters are characterized by the maximal within cluster spatial autocorrelation. To this purpose, for fixed values of C and m, it is advisable to run the clustering algorithm for increasing values of β (e.g. from 0 to β_{max}, with $\beta_{max} > 0$ chosen in advance and with increasing steps equal to β_{inc}) and to choose the optimal value of β in such a way that the within cluster spatial autocorrelation is maximized. The measure of *contiguity* correlation introduced to assess the post-cluster correlation between units, the Fuzzy Moran (FM)'s index, is a multivariate fuzzy generalisation of the Moran's index (Gittleman and Kot 1990). The idea of the FM index is to compute the correlation between classified units in which both the matrix of membership degrees and the *contiguity* matrix are considered (Coppi et al. 2010). The *contiguity* correlation measure ρ_c for the c−th cluster is:

$$\rho_c = \frac{tr(\mathbf{QX}_{comp})'\mathbf{U_c}^{0.5}\mathbf{PU_c}^{0.5}(\mathbf{QX}_{comp})}{tr(\mathbf{QX}_{comp})'\mathbf{U_c}^{0.5}\mathbf{P}'\mathbf{PU_c}^{0.5}(\mathbf{QX}_{comp})} \tag{5}$$

where $\mathbf{U}_c$ is the square diagonal matrix of order I of the membership degrees of cluster c; $\mathbf{X}_{comp}$ is the centred *compromise* matrix (mean of the $\mathbf{T}$ data matrices $\mathbf{X}_t$); $\mathbf{P}$ is the *contiguity* matrix. The matrix $\mathbf{Q}$, in which $\mathbf{Q} = \mathbf{I}_I - \frac{\mathbf{1}_I\mathbf{1}_I'}{I}$ is the centering operator, where $\mathbf{I}_I$ is an identity matrix of order I and $\mathbf{1}_I$ is a column-vector of order I with unit elements.

In order to determine an overall contiguity correlation measure for the obtained partition we can compute the weighted mean of the measures in (5) with weights s_c equal to the normalized sum over the I spatial units of the membership degrees in the C clusters:

$$\rho_{overall} = \frac{\sum_{c=1}^{C} \rho_c s_c}{\sum_{c=1}^{C} s_c} = \frac{\sum_{c=1}^{C} \rho_c s_c}{I}. \tag{6}$$

The contiguity correlation index ranges between − 1 and 1.

4 Application

The Fuzzy clustering model with the two dissimilarity measures introduced in Sect. 3 has been applied to the time array represented by 2 times (2013 and 2016), 3 variables (Basic, Efficiency, Innovation) and 256 units (EU NUTS). The interpretation of the clusters has considered all the 11 Pillars composing the RCI. A number of clusters from 3 to 10 has been considered and the number of clusters has been selected on the basis of the validity criteria illustrated in Sect. 3. The parameter β has been selected according to the correlation coefficient introduced in Sect. 3. The original 279 EU NUTS have been reduced to 256 by excluding the France NUTS Guadeloupe, Martinique, Guyane, Réunion, Mayotte and Malta (due to missing data) and taking into account the RCI 2016 time comparisons indications to harmonize the 2013 and 2016 NUTS classification.

The application of the models is described in Table 10. The Fuzzy C-Medoids model has been applied without contiguity constraints in the cross-sectional form at the times 2016 (Sect. 4.2) and 2013 (Sect. 4.3) and in the longitudinal form either binding the 2013 and 2016 indicators (Sect. 4.5) or computing the absolute and relative variations between 2016 and 2013 (Sect. 4.4). The Fuzzy C-Medoids model has been applied with contiguity constraints in the cross-sectional form at time 2016 using a geographic contiguity (Sect 4.6) and a level of GDP contiguity (Sect. 4.7).

Table 10 Models and applications (sections in parenthesis)

2013	2016	2013–2016
CS-FCMd (4.2)	CS-FCMd (4.3)	L-FCMd (4.5)
	CS-FCMd-C (geographic) (4.6)	L-FCMd absolute variation (4.4)
	CS-FCMd-C (GDP) (4.7)	L-FCMd relative variation (4.4)

4.1 Cross Sectional Fuzzy C-Medoids Clustering (CS-FCMd) RCI 2016

A first clustering has been developed on the basis of the univariate RCI 2016 index (Fig. 2). The EU establishes 8 classes of RCI 2016 and associates each class to a color in the maps published. The classes are: $(< -1.00), (-1.00; -0.50), (-0.50; -0.20), (-0.20;0.00), (0.00;0.20), (0.20;0.50), (0.50;1.00), (> 1.00)$ and the classes sizes are (1 2 3 4 5 6 7 8) (29 43 30 20 25 62 41 6).

The partition in 8 clusters obtained applying the CS-FCMd clustering model is a good partition with respect to the cluster validity index. The obtained centroids for the Fuzzy C-Medoids with 8 clusters are $(-1.32; -0.92; -0.59; -0.27;0.05;0.35;0.630.97)$ and the cluster sizes are (21 17 63 26 23 38 38 30). The medoids of the Fuzzy C-Medoids show the prevalence of low values of RCI 2016.

4.2 Cross Sectional Fuzzy C-Medoids Clustering (CS-FCMd) RCI 2016 Subindexes

The Sammon projection (Sammon 1969)[2] of the EU regions (Fig. 3) shows that the regions with high positive values of the three subindexes are in the left quadrants (UK00, UKJ1, NL31, SE11 at the most left); then moving to right there are the regions with positive values of the three subindexes; then the regions with negative values of the three subindexes and then the regions with high negative values of the three subindexes (RO22, EL51, EL64, BG31 at the most right). They are the four best and the four worst regions with respect to the value of the RCI. All the Italian regions have a negative value of the RCI (Table 7). It has to be noticed that all the Italian NUTS have negative values of the three subindexes with the exception of Lombardia in the Efficiency subindex.

The best partition is the 6 clusters partition according to the *FS* index (Sect. 3.2). The clusters are *very high negative* cluster 2 (medoid EL53), *high negative* cluster 1 (medoid SK04) and *medium negative* cluster 3 (medoid ITI3); *low positive* cluster 4 (medoid FR43), *medium positive* cluster 5 (medoid SE33) and *high positive* cluster 6 (medoid BE21). In the *high negative* cluster the worst subindex is the Basic; in the *high positive* cluster the best subindex is Innovation (Table 11). The intervals for very high, high, medium and low negative and positive—according to the RCI thresholds (Sect. 4.1) are—$(< -1.0);(-1.0; -0.5);(-0.5; -0.2);(-0.2; -0.0);(0.0;0.2);(0.2;0.5);(0.5;1.0);(> 1.0)$ (Fig. 2). Three clusters have negative values of the subindexes; three clusters have positive values of the subindexes.

[2] The Sammon projection is a projection of points onto a low-dimensional space aimed at minimising the error projection obtained summing up the squared differences (before versus after transformation) in pairwise distances between points

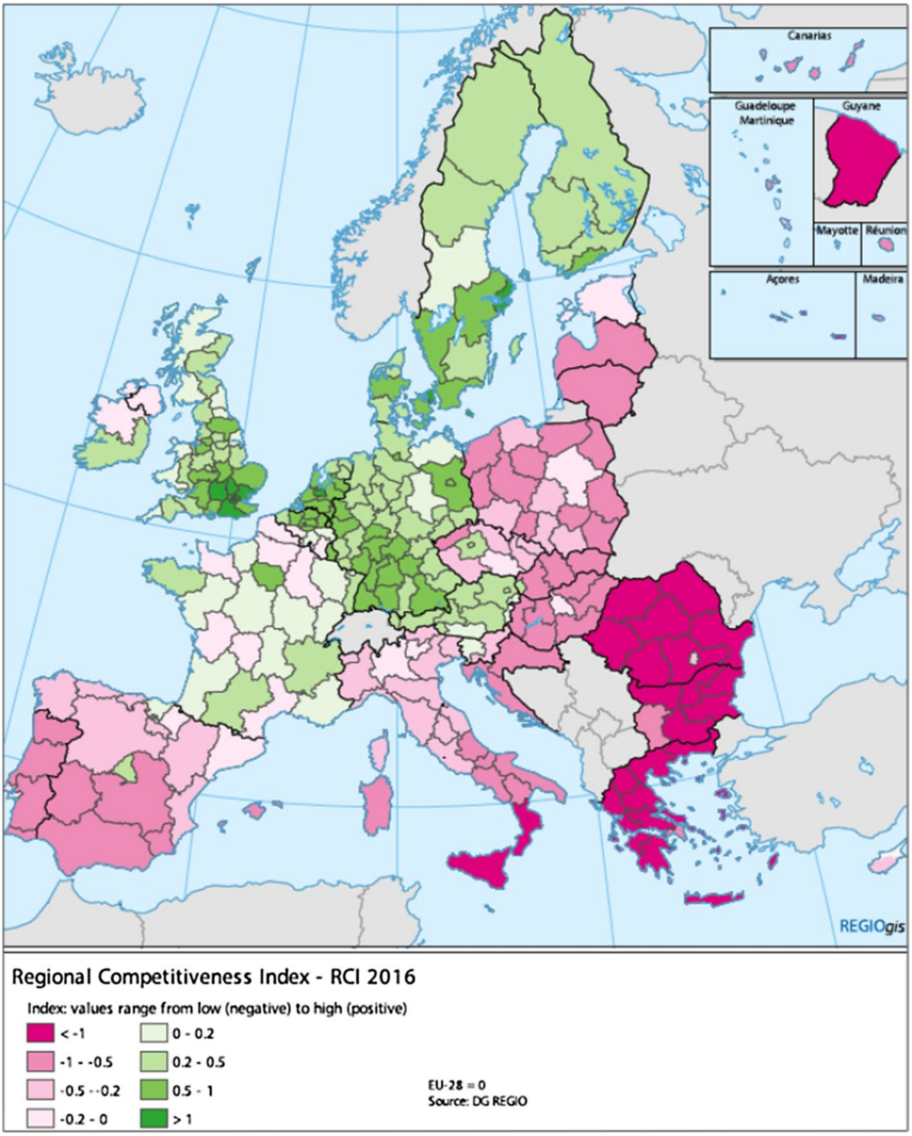

Fig. 2 RCI 2016—Annoni et al. (2017)

Regions Lombardia (ITC4) and Lazio (ITI4) are in cluster 4 (*low positive*), close in Fig. 3; the regions Campania (ITF3), Puglia (ITF4), Basilicata (ITF5), Calabria (ITF6), Sicilia (ITG1), Sardegna (ITG2) are in cluster 1 (*high negative*) and the others in cluster 3 (*medium negative*). The only region with membership smaller than 0.50 is ITH2 that shows 0.493 membership to cluster 2 and 0.462 to cluster 4 (Table 13).

The regions in cluster 1 (Table 12) are mostly regions of Spain (ES), Hungary (HU) and Italy (IT); the regions in cluster 2 mostly regions mostly regions of Bulgaria (BG), Greece (EL) and Romania (RO); the regions in cluster 3 mostly regions of Czech Republic (CZ),

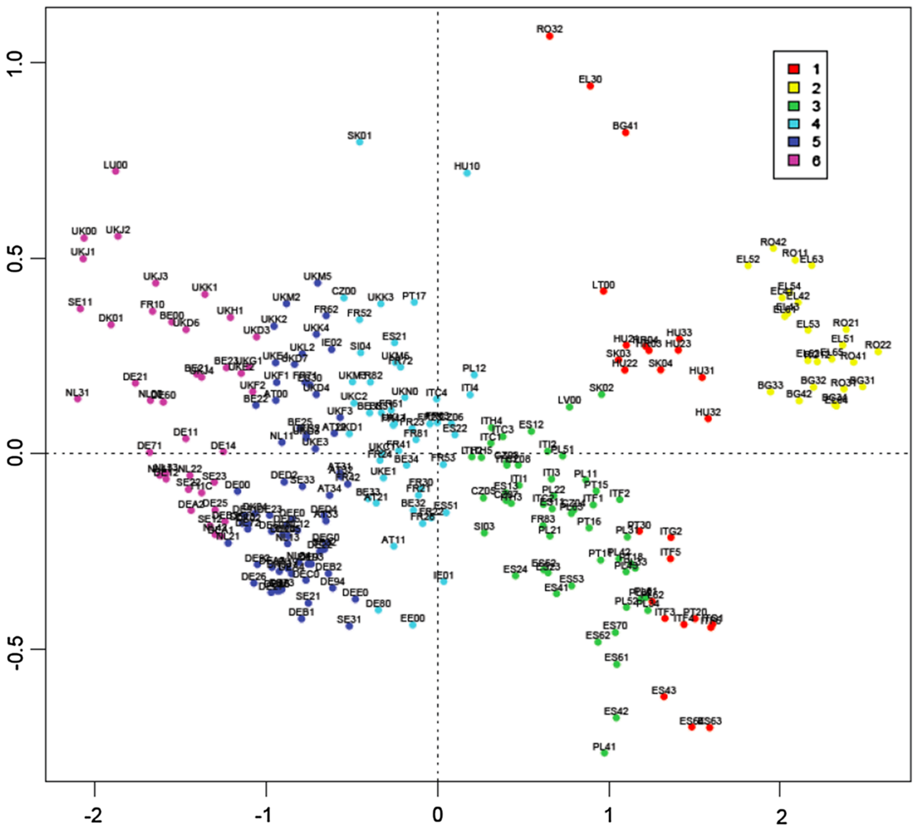

Fig. 3 Sammon projection of the NUTS and clustering

Table 11 Fuzzy C-medoids RCI 2016 clusters

Medoid	Basic	Efficiency	Innovation	
1 SK04 Východné Slovensko	− 0.943	− 0.811	− 0.777	ITF3, ITF4, ITF5 ITF6, ITG1, ITG2
2 EL53 Dytiki Makedonia	− 1.485	− 1.237	− 1.301	
3 ITI3 Marche	− 0.355	− 0.448	− 0.590	Others
4 FR43 Franche-Comté	0.017	0.074	0.094	ITC4, ITI4
5 SE33 Övre Norrland	0.434	0.278	0.396	
6 BE21 Antwerpen	0.526	0.722	0.902	

Spain (ES), Italy (IT) and Poland (PL); the regions in cluster 4 mostly regions of Belgium (BE), Spain (ES), France (FR) and United Kingdom (UK); the regions in cluster 5 mostly regions of Austria (AT), Germany (DE), Netherlands (NL) and United Kingdom (UK) and regions in cluster 6 mostly regions of Germany (DE), Netherland (NL), Sweden (SE) and United Kingdom (UK).

Table 12 Fuzzy C-medoids RCI 2016 cluster composition

	AT	BE	BG	CZ	DE	DK	EE	EL	ES	FI	FR	HR	HU	IE
Cluster 1			1					1	3			2	6	
Cluster 2			5					12						
Cluster 3				5					12		1			
Cluster 4		4		2	1		1		3		17		1	1
Cluster 5	2	2			26	4			1	3	3			1
Cluster 6	6	3			10	1				1	1			
	8	9	6	7	37	5	1	13	19	4	22	2	7	2
Gini heterogeneity	0.45	0.77	0.33	0.49	0.52	0.38	0.00	0.17	0.66	0.45	0.46	0.00	0.29	0.60
% in clusters 4–6	1.00	1.00	0.00	0.29	1.00	1.00	1.00	0.00	0.21	1.00	0.95	0.00	0.14	1.00

	IT	LT	LU	LV	NL	PL	PT	RO	SE	SI	SK	UK	
Cluster 1	6	1				1	2	1			2		26
Cluster 2								7					24
Cluster 3	13			1		14	4			1	1		52
Cluster 4	2					1	1			1	1	9	47
Cluster 5					5				4			13	68
Cluster 6			1		6				4			12	39
	21	1	1	1	11	16	7	8	8	2	4	34	256
Gini heterogeneity	0.63	0.00	0.00	0.00	0.60	0.27	0.69	0.26	0.60	0.60	0.75	0.79	
% in clusters 4–6	0.10	0.00	1.00	0.00	1.00	0.06	0.14	0.00	1.00	0.50	0.25	1.00	

For each country the normalized Gini heterogeneity index of dispersion (range in 0–1, 0 minimum heterogeneity) of the NUTS among the clusters is presented in Table 12 together with the percentage of NUTS in the clusters with positive values of the subindexes to join the information about the dispersion among clusters with the membership to good clusters. The indexes show that NUTS in *Western Europe* countries (Austria, Belgium, France, Germany, Ireland, Luxembourg, The Netherlands, United Kingdom) and in *Northern Europe* countries (Denmark, Estonia, Finland, Latvia, Lituania, Sweden) are sparsed among the good clusters.

The membership to all the clusters for the Italian regions is presented in Table 13; the highest membership (U) and related cluster for the NUTS is presented in Table 14.

As a general comment the regions of the NUTS1 level NORD-OVEST and NORD-EST perform better than the others.

Lombardia (ITC4) is the best performing among the 20 Italian regions with a standardized score equal to − 0.047, which corresponds to a rank of 158 out 263 (was 128th in 2013). As in 2013, the only positive score is reached in the Efficiency subindex (+ 0,045) even if it has deteriorated from + 0.114 registered three years before. With regard to the pillars the best position is reached in Health (rank 32th), followed by the Business Sophistication (rank 59th) and Infrastructure (rank 69th). It is worth noting that Lombardia is the most prosperous region in Italy, with a GDP per capita equal to 33,5 thousand euro about 31% higher than the European average. It is also the leading region in the Italian economy as measured by total production, export and employment representing over one fifth of the whole national value. Despite the strengths and

Table 13 Fuzzy C-Medoids RCI 2016 memberhip

Year	NUTS	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
2016	ITC1	0.017	0.001	**0.809**	0.159	0.012	0.002
2016	ITC2	0.000	0.000	**1.000**	0.000	0.000	0.000
2016	ITC3	0.013	0.001	**0.919**	0.060	0.005	0.001
2016	ITC4	0.002	0.000	0.025	**0.958**	0.013	0.002
2016	ITF1	0.053	0.001	**0.943**	0.002	0.001	0.000
2016	ITF2	0.375	0.008	**0.611**	0.005	0.001	0.000
2016	ITF3	**0.732**	0.061	0.191	0.011	0.004	0.001
2016	ITF4	**0.670**	0.117	0.191	0.014	0.005	0.002
2016	ITF5	**0.771**	0.048	0.172	0.006	0.002	0.001
2016	ITF6	**0.632**	0.211	0.139	0.012	0.005	0.002
2016	ITG1	**0.623**	0.224	0.134	0.012	0.005	0.002
2016	ITG2	**0.846**	0.042	0.104	0.005	0.002	0.001
2016	ITH1	0.020	0.002	**0.894**	0.072	0.010	0.002
2016	ITH2	0.015	0.002	**0.493**	0.462	0.025	0.004
2016	ITH3	0.005	0.000	**0.977**	0.016	0.002	0.000
2016	ITH4	0.018	0.001	**0.804**	0.163	0.012	0.002
2016	ITH5	0.015	0.001	**0.695**	0.269	0.017	0.003
2016	ITI1	0.003	0.000	**0.989**	0.006	0.001	0.000
2016	ITI2	0.000	0.000	**1.000**	0.000	0.000	0.000
2016	ITI3	0.000	0.000	**1.000**	0.000	0.000	0.000
2016	ITI4	0.020	0.002	0.325	**0.619**	0.030	0.005

Bold values indicate highest membership

resiliency of its economy during the global recession, Lombardia faces critical challenges: improving the overall educational attainment levels and upgrading the skills of the regional population by aligning higher education provision with the needs and opportunities of the region and its SMEs (OECD 2011). The region is undergoing an industrial shift towards services and knowledge-intensive activities and the manufacturing firms will need to focus on differentiation and a more intense use of knowledge. The success of this emerging manufacturing model relies on the access to skilled and qualified labour: in 2016 the percentage of population aged 25–64 with a tertiary educational attainment is 19.3% (215th the rank) compared to 74.8% of Inner London, the best competitive region in Europe (Eurostat database).

Lazio (ITI4) is indeed the administrative centre of Italy and therefore the business sector is less important than in most of the other central and northern Italian regions. Lazio is the Italian region that is more oriented towards services: about 85% of its value added (at current market prices) is related to services, of which 33% to financial and insurance, real estate, professional, scientific and technical activities. As regard to Basic subindex, Lazio in recent years has taken effective actions in order to enhance the quality of their institutions (247th its rank) by simplifying the life of citizens and enterprises: a single SUAP (One stop shop for Production Activities) with a single information system, same forms to be used everywhere in the region, a homogeneous offer with services for all the Lazio towns. Furthermore, Lazio has implemented a plurality of interventions supporting the

Table 14 Fuzzy C-Medoids membership of the NUTS

	NUTS	Cluster	U		NUTS	Cluster	U		NUTS	Cluster	U		NUTS	Cluster	U
1	AT11	4	0.891	33	DE12	6	0.971	65	DEE0	5	0.641	97	ES43	1	0.505
2	AT00	5	0.878	34	DE13	5	0.653	66	DEF0	5	0.998	98	ES51	4	0.799
3	AT21	4	0.918	35	DE14	6	0.839	67	DEG0	5	0.928	99	ES52	3	0.969
4	AT22	5	0.803	36	DE21	6	0.980	68	DK01	6	0.953	100	ES53	3	0.883
5	AT31	5	0.738	37	DE22	5	0.914	69	DK02	5	0.793	101	ES61	3	0.508
6	AT32	5	0.790	38	DE23	5	0.975	70	DK03	5	0.942	102	ES62	3	0.742
7	AT33	5	0.951	39	DE24	5	0.977	71	DK04	5	0.882	103	ES63	1	0.493
8	AT34	5	0.955	40	DE25	6	0.789	72	DK05	5	0.995	104	ES64	1	0.492
9	BE00	6	0.977	41	DE26	5	0.807	73	EE00	4	0.699	105	ES70	3	0.604
10	BE11	6	1.000	42	DE27	5	0.870	74	EL30	1	0.602	106	FI19	5	0.981
11	BE22	5	0.516	43	DE00	5	0.521	75	EL41	2	0.984	107	FI1C	6	0.905
12	BE23	6	0.958	44	DE50	5	0.960	76	EL42	2	0.999	108	FI1D	5	0.969
13	BE25	5	0.886	45	DE60	6	0.992	77	EL43	2	0.988	109	FI20	5	0.922
14	BE32	4	0.943	46	DE71	6	0.974	78	EL51	2	0.994	110	FR10	6	0.972
15	BE33	4	0.811	47	DE72	5	0.769	79	EL52	2	0.782	111	FR21	4	0.976
16	BE34	4	0.993	48	DE73	5	0.954	80	EL53	2	1.000	112	FR22	4	0.905
17	BE35	4	0.979	49	DE80	4	0.580	81	EL54	2	0.998	113	FR23	4	0.987
18	BG31	2	0.986	50	DE91	5	0.695	82	EL61	2	0.996	114	FR24	4	0.957
19	BG32	2	0.988	51	DE92	5	0.899	83	EL62	2	0.999	115	FR25	4	0.965
20	BG33	2	0.895	52	DE93	5	0.975	84	EL63	2	0.986	116	FR26	4	0.897
21	BG34	2	0.987	53	DE94	5	0.860	85	EL64	2	0.995	117	FR30	4	0.972
22	BG41	1	0.720	54	DEA1	6	0.610	86	EL65	2	0.998	118	FR41	4	0.999
23	BG42	2	0.961	55	DEA2	6	0.918	87	ES11	3	0.999	119	FR42	5	0.547
24	CZ00	4	0.649	56	DEA3	5	0.917	88	ES12	3	0.997	120	FR43	4	1.000
25	CZ03	3	0.965	57	DEA4	5	0.965	89	ES13	3	0.969	121	FR51	4	0.960
26	CZ04	3	0.995	58	DEA5	5	0.927	90	ES21	4	0.948	122	FR52	4	0.820
27	CZ05	3	0.761	59	DEB1	5	0.872	91	ES22	4	0.756	123	FR53	4	0.924

Table 14 (continued)

	NUTS	Cluster	U		NUTS	Cluster	U		NUTS	Cluster	U		NUTS	Cluster	U
28	CZ06	4	0.885	60	DEB2	5	0.917	92	ES23	3	0.989	124	FR61	4	1.000
29	CZ07	3	0.969	61	DEB3	6	0.601	93	ES24	3	0.937	125	FR62	5	0.506
30	CZ08	3	0.989	62	DED2	5	0.998	94	ES30	5	0.903	126	FR63	4	0.957
31	DEC0	5	0.974	63	DED4	5	0.983	95	ES41	3	0.978	127	FR71	5	0.877
32	DE11	6	0.990	64	DED5	5	0.996	96	ES42	3	0.594	128	FR72	4	0.995
	NUTS	Cluster	U		NUTS	Cluster	U		NUTS	Cluster	U		NUTS	Cluster	U
129	FR81	4	0.996	161	ITI2	3	1.000	193	PL63	3	0.977	225	UKD1	4	0.662
130	FR82	4	0.982	162	ITI3	3	1.000	194	PT11	3	0.842	226	UKD3	6	0.715
131	FR83	3	0.991	163	ITI4	4	0.619	195	PT15	3	0.886	227	UKD4	5	0.887
132	HR03	1	1.000	164	LT00	1	0.612	196	PT16	3	0.966	228	UKD6	6	0.997
133	HR04	1	0.999	165	LU00	6	0.836	197	PT17	4	0.914	229	UKD7	5	0.852
134	HU10	4	0.533	166	LV00	3	0.938	198	PT18	3	0.584	230	UKE1	4	0.981
135	HU21	1	0.853	167	NL11	5	0.980	199	PT20	1	0.677	231	UKE2	6	0.873
136	HU22	1	0.872	168	NL12	5	0.997	200	PT30	1	0.718	232	UKE3	5	0.993
137	HU23	1	0.996	169	NL13	5	0.992	201	RO11	2	0.935	233	UKE4	5	0.714
138	HU31	1	0.960	170	NL21	5	0.508	202	RO12	2	0.986	234	UKF1	5	0.816
139	HU32	1	0.912	171	NL22	6	0.970	203	RO21	2	0.961	235	UKF2	6	0.621
140	HU33	1	0.965	172	NL00	6	0.989	204	RO22	2	0.979	236	UKF3	5	0.557
141	IE01	4	0.736	173	NL31	6	0.903	205	RO31	2	0.976	237	UKG1	6	0.795
142	IE02	5	0.558	174	NL33	6	0.974	206	RO32	1	0.355	238	UKG2	5	0.980
143	ITC1	3	0.809	175	NL34	5	0.966	207	RO41	2	0.957	239	UKG3	5	0.908
144	ITC2	3	1.000	176	NL41	6	0.968	208	RO42	2	0.924	240	UKH1	6	0.873
145	ITC3	3	0.919	177	NL42	6	0.690	209	SE11	6	0.913	241	UK00	6	0.881
146	ITC4	4	0.958	178	PL11	3	0.924	210	SE12	6	0.779	242	UKJ1	6	0.907
147	ITF1	3	0.943	179	PL12	4	0.478	211	SE21	5	0.880	243	UKJ2	6	0.939

Table 14 (continued)

	NUTS	Cluster	U		NUTS	Cluster	U		NUTS	Cluster	U		NUTS	Cluster	U
148	ITF2	3	0.611	180	PL21	3	0.955	212	SE22	6	0.950	244	UKJ3	6	0.984
149	ITF3	1	0.732	181	PL22	3	0.893	213	SE23	6	0.879	245	UKJ4	6	1.000
150	ITF4	1	0.670	182	PL31	3	0.643	214	SE31	5	0.657	246	UKK1	6	0.978
151	ITF5	1	0.771	183	PL32	3	0.561	215	SE32	5	0.939	247	UKK2	5	0.521
152	ITF6	1	0.632	184	PL33	3	0.595	216	SE33	5	1.000	248	UKK3	4	0.803
153	ITG1	1	0.623	185	PL34	3	0.495	217	SI03	3	0.791	249	UKK4	5	0.678
154	ITG2	1	0.846	186	PL41	3	0.825	218	SI04	4	0.883	250	UKL1	4	0.986
155	ITH1	3	0.894	187	PL42	3	0.742	219	SK01	4	0.584	251	UKL2	5	0.813
156	ITH2	3	0.493	188	PL43	3	0.674	220	SK02	3	0.637	252	UKM2	5	0.564
157	ITH3	3	0.977	189	PL51	3	0.991	221	SK03	1	0.935	253	UKM3	4	0.788
158	ITH4	3	0.804	190	PL52	3	0.684	222	SK04	1	1.000	254	UKM5	5	0.505
159	ITH5	3	0.695	191	PL61	3	0.5 15	223	UKC1	4	0.962	255	UKM6	4	0.991
160	ITI1	3	0.989	192	PL62	1	0.475	224	UKC2	4	0.712	256	UKN0	4	0.913

Table 15 Fuzzy C-Medoids RCI 2013 clusters

Medoid	Basic	Efficiency	Innovation	
BG33 Severoiztochen	− 1.360	− 1.232	− 1.332	
ES13 Cantabria	− 0.141	− 0.255	− 0.439	Others
PL42 Zachodniopomorskie	− 0.434	− 0.821	− 0.885	ITF1, ITF2, ITF3
				ITF4, ITF5, ITF6
				ITG1, ITG2
DE11 Stuttgart	0.693	0.841	0.975	
FR23 Haute-Normandie	0.002	− 0.226	0.077	ITC4, ITI4
DE23 Oberpfalz	0.485	0.414	0.426	

reconversion of the productive system based on strengthening the networks and consortia of enterprises and supporting the propensity to innovate and the technological transfer. With respect to Innovation subindex, Lazio with a score of − 0.08 (143th) has performed even better than Lombardia (− 0.12, 148th). This result depends from the fact that it is a unique research and knowledge area in Italy and, indeed, presents a high concentration of public and private research institutes, technological poles and University institutions on an international level: there are more than 200 research laboratories, more than 40 public research institutes, 6 public universities, and 4 Centres of Excellence, such as the National Research Council (with more than 50 departments), ENEA (Institute for Energy), the National Institute for Nuclear Physics and the National Institute of Health. In total, the public sector employs 72% of total R&D staff. Human resources involved in research and development amounted to 150,700 about 6.5% of the total active population, higher than the Italian (6.1%) and European (5.8%) average. But patenting activity is however weak: only 24 patents per million inhabitants where generated in 2012, significantly less than the Italian (60) and European (112) average. Finally, with respect to the diffusion of ICTs, in 2016, Lazio has registered a good percentage of households with internet broadband access (81%), above the Italian average (77%) and not so far from the one for Europe (88%).

It important to underline that the decline of the scores for Abruzzo in 2016 is influenced by the devastating earthquake which occurred in 2009. Abruzzo (ITF1) is the one of the most industrialised region in Southern Italy (34.2% the share of value added from industry): the industrialisation rate is above the Italian average (73 enterprises per 1000 residents vs. a national average of 72).

4.3 Cross Sectional Fuzzy C-Medoids Clustering (CS-FCMd) RCI 2013 Subindexes

In 2013 the Italian regions except Lombardia (ITC4) have e negative value of the RCI. Lombardia (ITC4), Emilia Romagna (ITH5), Lazio (ITI4) and Puglia (ITF4), Calabria (ITF6), Sicilia (ITG1) are the three best and three worst italian regions with respect to the value of the RCI.

The best partition is the 6 clusters partition according to the *FS* index (Sect. 3.2). The clusters are *very high negative* cluster 1 (medoid BG33), *high negative* cluster 3 (medoid PL42) and *medium negative* cluster 2 (medoid ES13); *low positive* cluster 5 (medoid FR23),*medium positive* cluster 6 (medoid DE23) and *high positive* cluster 4 (medoid DE11). In the *low negative* cluster all the subindexes have a value smaller than − 1.00 and

Table 16 Fuzzy C-Medoids RCI 2013 memberhip

Year	NUTS	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
2013	ITC1	0.000	**0.927**	0.002	0.000	0.069	0.001
2013	ITC2	0.001	**0.886**	0.097	0.000	0.013	0.001
2013	ITC3	0.000	**0.782**	0.004	0.000	0.210	0.003
2013	ITC4	0.000	0.041	0.001	0.001	**0.952**	0.006
2013	ITF1	0.004	0.323	**0.657**	0.000	0.014	0.002
2013	ITF2	0.002	0.015	**0.982**	0.000	0.001	0.000
2013	ITF3	0.008	0.030	**0.955**	0.000	0.006	0.001
2013	ITF4	0.013	0.012	**0.971**	0.000	0.003	0.001
2013	ITF5	0.003	0.003	**0.993**	0.000	0.000	0.000
2013	ITF6	0.019	0.010	**0.968**	0.000	0.002	0.000
2013	ITG1	0.062	0.031	**0.895**	0.001	0.008	0.002
2013	ITG2	0.006	0.013	**0.978**	0.000	0.002	0.000
2013	ITH1	0.000	**0.988**	0.007	0.000	0.004	0.000
2013	ITH2	0.000	**0.930**	0.003	0.000	0.064	0.002
2013	ITH3	0.000	**0.997**	0.001	0.000	0.002	0.000
2013	ITH4	0.000	**0.938**	0.004	0.000	0.056	0.001
2013	ITH5	0.001	**0.648**	0.010	0.002	0.329	0.011
2013	ITI1	0.000	**0.983**	0.002	0.000	0.014	0.000
2013	ITI2	0.000	**0.986**	0.008	0.000	0.006	0.000
2013	ITI3	0.001	**0.920**	0.065	0.000	0.013	0.001
2013	ITI4	0.000	0.123	0.004	0.001	**0.866**	0.006

Bold values indicate highest membership

the worst subindexes are Basic and Innovation; in the *high positive* cluster all the subindexes have a value between 0,50 and 1,00 and the best subindex is Innovation (Table 15).

Regions Lombardia (ITC4) and Lazio (ITI4) are in cluster 5 (*low positive*); the regions Abruzzo (ITF1), Molise (ITF2), Campania (ITF3), Puglia (ITF4), Basilicata (ITF5), Calabria (ITF6), Sicilia (ITG1), Sardegna (ITG2) are in cluster 3 (*medium negative*) and the others in cluster 2 (*low negative*). It has to be noticed that all the Italian NUTS have negative values of the three subindexes with the exception of Lombardia (ITC4) and Emilia Romagna (ITH5) in the Efficiency subindex and Lazio (ITI4) in the Innovation subindex.

The membership to all the clusters for Italian regions is presented in Table 16.

All the Italian regions have a value of RCI in 2016 smaller than in 2013 with the exception of Bolzano (ITH1), even if some regions have improved the value of a subindex.

4.4 Longitudinal Fuzzy C-Medoids Clustering (L-FCMd) RCI Subindexes (Absolute and Percentual Variation 2013–2016)

The histogram of the absolute variations in the subindexes Basic, Efficiency and Innovation for the 256 NUTS are presented in Fig. 4. The modal class of the absolute variations among the EU RCI classes (Sect. 4.1) is (0.0; 0.2) for the Basic subindex; (− 0.20; 0.00) for the Efficiency and Innovation subindex. Positive variations 2013–2016 are registered

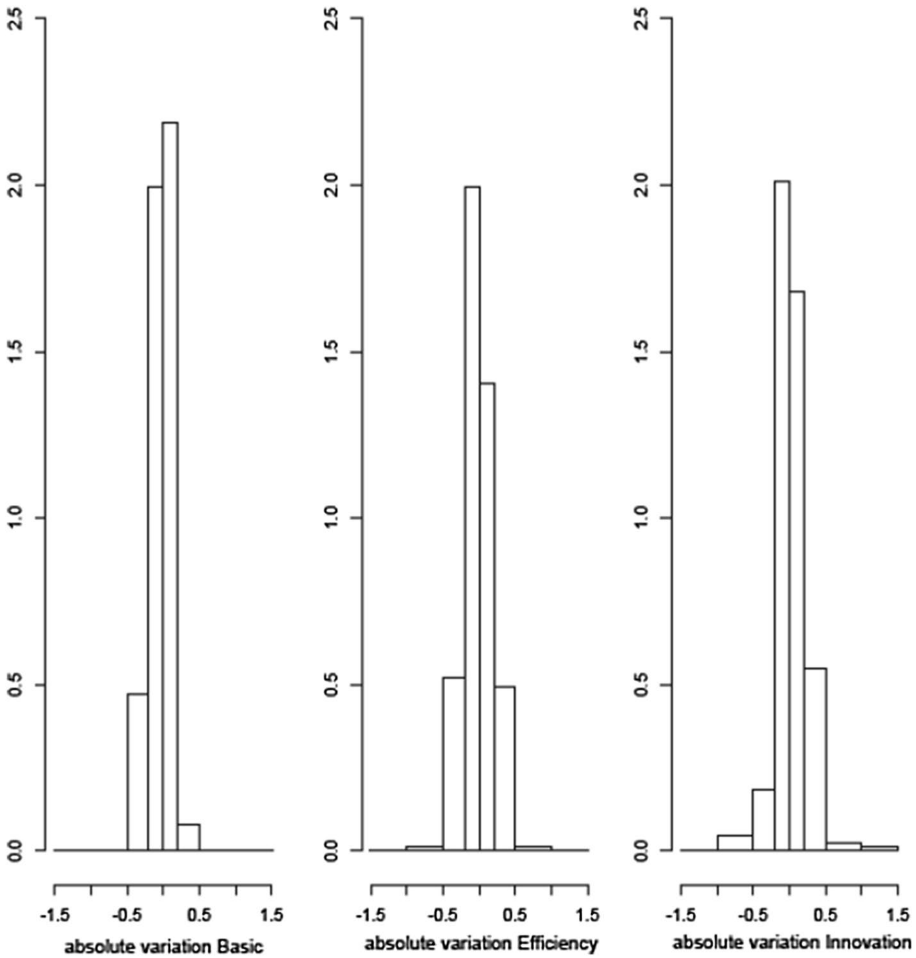

Fig. 4 Subindexes absolute variation 2013–2016

mostly in the Basic subindex. The absolute and percentual variations 2013–2016 for Italy with respect to the 3 subindexes are presented in Table 8.

The best partition according to the *FS* index (Sect. 3.2) is the 5 clusters partition. The five clusters have in general small negative values of the absolute variation 2013–2016 for each subindex. Beside two small negative values, cluster 1 *medium positive efficiency* (medoid FR83) shows a medium positive variation in the subindex Efficiency; cluster 2 *low positive innovation* (medoid PT17) a small positive variation in the subindex Innovation; cluster 3 *medium negative efficiency* (medoid ITC3) a medium negative variation in the subindex Efficiency; cluster 4 *medium positive innovation* (medoid UKH1) a medium positive variation in the subindex Innovation; cluster 5 *low positive efficiency* (medoid RO21) shows a small positive variation in the subindex Efficiency (Table 17).

Italian regions Lombardia (ITC1), Valle d'Aosta (ITC2), Molise (ITF2), Trento (ITH2), Friuli Venezia Giulia (ITH4), Marche (ITI3) are in cluster 2 *low positive innovation*. Italian regions Lombardia (ITC4), Basilicata (ITF5), Veneto (ITH3) and Lazio

Table 17 Fuzzy C-Medoids RCI absolute variation 2013–2016 clusters

Medoid	Basic	Efficiency	Innovation	
1 FR83 Corse	– 0.030	0.239	– 0.022	ITH1
2 PT17 Lisboa	– 0.014	– 0.069	0.068	ITC1, ITC2, ITF2
				ITH2, ITH4, ITI3
3 ITC3 Liguria	– 0.096	– 0.217	– 0.071	Others
4 UKH1 East Anglia	– 0.009	– 0.055	0.329	
5 RO21 Nord-Est (RO)	– 0.020	0.005	– 0.003	ITC4, ITF5, ITH3, ITI4

Table 18 Fuzzy C-Medoids absolute variation membership

Year	NUTS	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
2013–2016	ITC1	0.004	**0.450**	0.326	0.005	0.215
2013–2016	ITC2	0.000	**0.999**	0.000	0.000	0.001
2013–2016	ITC3	0.000	0.000	**1.000**	0.000	0.000
2013–2016	ITC4	0.006	0.290	0.105	0.003	**0.595**
2013–2016	ITF1	0.003	0.358	**0.547**	0.007	0.084
2013–2016	ITF2	0.000	**0.977**	0.001	0.000	0.022
2013–2016	ITF3	0.016	0.073	**0.808**	0.008	0.094
2013–2016	ITF4	0.011	0.113	**0.730**	0.006	0.140
2013–2016	ITF5	0.127	0.074	0.028	0.004	**0.767**
2013–2016	ITF6	0.018	0.095	**0.768**	0.011	0.108
2013–2016	ITG1	0.048	0.129	**0.586**	0.014	0.223
2013–2016	ITG2	0.017	0.082	**0.742**	0.006	0.153
2013–2016	ITH1	**0.987**	0.002	0.000	0.000	0.010
2013–2016	ITH2	0.002	**0.536**	0.006	0.001	0.455
2013–2016	ITH3	0.007	0.384	0.184	0.005	**0.421**
2013–2016	ITH4	0.001	**0.877**	0.017	0.001	0.104
2013–2016	ITH5	0.006	0.158	**0.756**	0.013	0.067
2013–2016	ITI1	0.006	0.138	**0.750**	0.006	0.100
2013–2016	ITI2	0.003	0.112	**0.782**	0.002	0.101
2013–2016	ITI3	0.002	**0.730**	0.023	0.002	0.243
2013–2016	ITI4	0.014	0.181	0.279	0.005	**0.520**

Bold values indicate highest membership

(ITI4) are in cluster 5 *low positive efficiency*. All the other Italian regions are in cluster 3 *medium negative efficiency*. Two regions have a membership less than 0.50 (Table 18): ITH3 0.421 to cluster 4 and 0.384 to cluster 2; ITC1 0.450 to cluster 2 and 0.326 to cluster 3. The regions in cluster 1 are mostly (first three) regions of France (FR), Poland (PL) and Sweden (SE); the regions in cluster 2 mostly regions of Germany (DE), Spain (ES) and Italy (IT); the regions in cluster 3 mostly regions of Greece (EL), Hungary (HU) and Netherland (NL); the regions in cluster 4 mostly regions of Czech Republic

Table 19 Fuzzy C-medoids RCI relative variation 2013–2016 clusters

Medoid	Basic	Efficiency	Innovation	
1 LV00 Latvija	0.150	0.442	0.331	ITH1
2 CZ07 Strední Morava	0.407	0.233	0.418	
3 AT22 Steiermark	3.889	0.423	0.887	
4 AT32 Salzburg	2.731	0.257	1.150	
5 PL52 Opolskie	– 0.006	– 0.110	– 0.057	Others

(CZ), Germany (DE) and United Kingdom (UK); the regions in cluster 5 mostly regions of Germany (DE).

The L-FCMd model has been applied also to the percentual variations 2013–2016 (Table 19).

Considering Italian regions in the Fuzzy C-Medoids Bolzano (ITH1) is alone in cluster 1 *medium positive efficiency* while all the others are in cluster 5 characterized by small negative percentual variations. The interpretation of the obtained clusters is based also on Table 8.

Bolzano (ITH1) turns out to be the first region of Italy with the highest GDP per capita: 39,400 EUR in PPs 2014, about 150% of the Italian and the EU average values. The level of relative wealth has increased with respect to 2008 (37,200), even though the global financial crisis affected the region. This strong resilience shown by the regional economy helps us to explain the impressive variation registered in the efficiency pillar in RCI 2016 compared to 2013. The labour productivity, the GDP per person employed in industry and services in terms of index with the EU20 = 100, has improved significantly reaching the level of 123.6 in 2014 (i.e. the reference year for RCI 2016) from 112.5 in 2011 (the reference year for RCI 2013). It's worth noting that this upgrading in the efficiency of productive system happened even in presence of an expansion of the person employed (+ 4 thousand the absolute increase), the denominator of the labour productivity. The share of population aged 15–24 not in education, employment or training (NEET[3]) in percentage of population aged 15–24 is the lowest among the Italian regions 9.7% compared with a national average of 24.1% and an European incidence of 14.2%. As regard to the pillar market size, the net adjusted disposable household income in PPCS per capita with index EU28 = 100 is the highest among all the other regions and equal to 133 in line with the Île de France the most competitive region of France and ranked eighth out 263 European regions.

All the other Italian regions show negative scores in all the macro-pillar in both 2016 and 2013 with the exception of Lombardia (ITC4) and Emilia Romagna (ITH5). However, by analysing the percentage variations we discover quite encouraging improvements even in the southern regions. For example Calabria (ITF6), the worst performing Italian region together with Sicilia (ITG1) (235th and 237th, respectively), shows an upgrading (+ 5.1%) exactly where it was in the latest i.e. in the Basic subindex position (217th in 2016 ranking

[3] The indicator young people neither in employment nor in education and training, abbreviated as NEET, corresponds to the percentage of the population of a given age group and sex who is not employed and not involved in further education or training. The numerator of the indicator refers to persons meeting these two conditions: they are not employed (i.e. unemployed or inactive according to the International Labour Organisation definition); they have not received any education or training in the four weeks preceding the survey. The denominator is the total population of the same age group and sex, excluding the respondents who have not answered the question 'participation to regular education and training'.

Table 20 Fuzzy C-Medoids RCI 2013–2016 clusters

Medoid	2013			2016		
	Basic	Efficiency	Innovation	Basic	Efficiency	Innovation
1 EL42 N. Aigaio	− 1.298	− 1.422	− 1.354	− 1.498	− 1.083	− 1.330
2 BE21 Antwerpen	0.647	0.852	0.838	0.526	0.722	0.902
3 ITF1 Abruzzo	− 0.427	− 0.469	− 0.729	− 0.439	− 0.651	− 0.726
4 DE23 Oberpfalz	0.485	0.414	0.426	0.601	0.387	0.460
5 FR41 Lorraine	0.030	− 0.094	− 0.051	0.054	0.081	0.008

from 226th in 2013), followed by Puglia (ITF4) with a relative increase of around 4.0% compared to 2013.

For Calabria (ITF6) the improvement in the basic pillar is due to an increase in the trust towards local public authorities, a reduction in early school leavers rate (from 16.2 to 15.7%), an upgrading in reading (from 184.0 in 2012 to 192.0 in 2015) and mathematics (from 186.9 in 2012 to 194.2 in 2015) proficiency scores of lower and upper secondary students, that all in one were able to more than offset the worsening in the duration of civil disputes (from 758.7 days to 846.2) and the widening in the share of NEET (from 35.8 to 38.2%). By contrast Puglia shows an improvement in all the indicators explaining the basic pillar, especially in the efficiency of justice wherein the duration of civil disputes has decreased from 951.9 to 798.8 days.

4.5 Longitudinal Fuzzy C-Medoids Clustering (L-FCMd) RCI 2013–2016 Subindexes

The best partition according to the *FS* index (Sect. 3.2) is the 5 clusters partition. The values of the weights w_t that optimize 1 are 0.4 and 0.6 for $t = 2013, 2016$, respectively.

Two clusters have negative values of the subindexes, cluster 1 (medoid EL42) with all subindexes smaller than − 1.00 and cluster 3 (medoid ITF1) with the subindexes in the interval (− 0.50; − 1.00); cluster 5 (medoid FR41) has two negative subindexes (Efficiency 2013 and Innovation 2013) and the other positive but all close to 0.00; two clusters have positive values of the subindexes, cluster 4 (medoid DE23) in the interval (0.20; 0.50) and cluster 2 (medoid BE21) in the interval (0.50; 1.00) (Table 20).

Italian regions Piemonte (ITC1), Liguria (ITC3), Lombardia (ITC4), Trento (ITH2), Friuli Venezia Giulia (ITH4), Emilia Romagna (ITH5) and Lazio (ITI4) are in cluster 5. All the other Italian regions are in cluster 3.

4.6 Cross Sectional Fuzzy C-Medoids (CS-FCMd-C) RCI 2016 Subindexes with *Contiguity* Constraints: Regions of Europe

The NUTS are grouped into 4 geographic areas: Western Europe, Southern Europe, Central Europe and Northern Europe.

- *Western Europe—area 1*: Austria, Belgium, France, Germany, Ireland, Luxembourg, The Netherlands, United Kingdom
- *Southern Europe—area 2*: Cyprus, Greece, Italy, Malta, Portugal, Spain

Table 21 Fuzzy C-Medoids RCI 2016 clusters with geographic area contiguity constraint

Medoid	Basic	Efficiency	Innovation	
1 CZ06 Jihovýchod	– 0.165	– 0.147	– 0.093	
2 ITF2 Molise	– 0.530	– 0.657	– 0.885	Others
3 ITI4 Lazio	– 0.287	– 0.241	– 0.081	ITI4
4 NL11 Groningen	0.405	0.445	0.464	

Table 22 Fuzzy C-Medoids RCI 2016 with geographic area constraint cluster composition

	AT	BE	BG	CZ	DE	DK	EE	EL	ES	FI	FR	HR	HU	IE
Cluster 1				1										
Cluster 2			6	6				13	19			2	7	
Cluster 3														
Cluster 4	8	9			37	5	1			4	22			2
	8	9	6	7	37	5	1	13	19	4	22	2	7	2
	IT	LT	LU	LV	NL	PL	PT	RO	SE	SI	SK	UK		
Cluster 1													1	
Cluster 2	20					16	7	8		2	4		110	
Cluster 3	1												1	
Cluster 4		1	1	1	11				8			34	144	
	21	1	1	1	11	16	7	8	8	2	4	34	256	

- *Central Europe—area 3*: Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia
- *Northern Europe—area 4*: Denmark, Estonia, Finland, Latvia, Lituania, Sweden

To take into account the geographic area the clustering model has been applied with a contiguity matrix based on the area. The clustering into four groups has been considered according to the *FS* index (Sect. 3.2). The spatial parameter β has been selected in the interval 0.5–4.0 (step 0.5) in such a way that the within cluster spatial autocorrelation measure is maximized (Sect. 3.2). The selected value of β is equal to 0.3.

In the Fuzzy C-Medoids three clusters have negative values of the subindexes and one cluster positive values. In cluster 1 (medoid CZ06) the three subindexes have negative values in the interval (0.00; $-$ 0.20); in cluster 2 (medoid ITF2) the three subindexes are negative in the interval ($-0,50$; $-$ $1,00$); in cluster 3 (medoid ITI4) the subindexes Basic and Efficiency are negative in the interval (-0.20; $-$ 0.50) and the subindex Innovation in the interval (-0.00; $-$ 0.20); in cluster 4 (medoid NL11) the three subindexes have positive values in the interval (0.20; 0.50) (Table 21).

The Italian region Lazio (ITI4) is in cluster 3 (highest value in Italy of the subindex Innovation); all the other regions are in cluster 2. Except Lazio (ITI4)—single in cluster 3—the Italian regions are in clusters homogeneous with respect to the area.

The region in cluster 1 is CZ06; the regions in cluster 2 are mostly (first three) regions of Spain (ES), Italy (IT) and Poland (PL); the region in cluster 3 is ITI4; the regions in cluster 4 mostly regions of Germany (DE), France (FR) and United Kingdom (UK) (Table 22).

Table 23 Fuzzy C-Medoids RCI 2016 with geographic area constraint cross-table cluster/area

	Area 1	Area 2	Area 3	Area 4	
Cluster 1			1		1
Cluster 2		59	51		110
Cluster 3		1			1
Cluster 4	124			20	144
	124	60	52	20	256

The cross-table geographic area/cluster presented in Table 23 shows geographic area homogeneity. The regions in areas 2 and 3 (Southern/Central Europe) are in cluster 2; the regions in areas 1 and 4 (Western/Northern Europe) are in cluster 4.

4.6.1 Comparison with RCI 2016 Clustering Without Constraints

The comparison with the clusters RCI 2016 without the constraint on the geographic area (Sect. 4.2) shows an upgrade for regions Campania (ITF3) to Sardegna (ITG2); a downgrade for all the other regions. This means that Italian regions in geographic area 2 are in clusters with regions—in the same area—performing better with respect to regions Campania (ITF3) to Sardegna (ITG2) and worst with respect to all the others.

4.7 Cross Sectional Fuzzy C-Medoids (CS-FCMd-C) RCI 2016 Subindexes with *Contiguity* Constraints: Level of GDP

The RCI is obtained as an average of the subindexes Basic, Efficiency and Innovation with weights depending on the stage of development (Tables 4, 6). To take into account the stage of development the clustering models have been applied with a contiguity matrix based on the five levels of development. The clustering into five groups has been considered according to the *FS* index (Sect. 3.2). The selected value of the spatial parameter β is equal to 0.5 (Sect. 3.2). The Fuzzy C-Medoids partition is presented.

In cluster 3 (medoid HU32) the three subindexes have negative values, Basic and Efficiency in the interval (-0.50; -1.00) and Innovation smaller than -1.00; in clusters 1 (medoid FR21) and 2 (medoid FR81) two subindexes have a small negative values and one a small positive values, Basic in cluster 1 and Innovation in cluster 2; in cluster 4 (medoid NL11) the three subindexes have positive values in the interval (0.20; 0.50) and in cluster 5 (medoid UKD1) the subindexes Basic and Efficiency have positive values in the interval (0.00; 0.20) and the Innovation subindex in the interval (0.20; 0.50) (Table 24).

The Italian regions Abruzzo (ITF1), Molise (ITF2) and Umbria (ITI2) (GDP level 3) are in cluster 2; regions ITC2, Lombardia (ITC4), Bolzano (ITH1), Trento (ITH2), Veneto (ITH3), Emilia Romagna (ITH5) and Lazio (ITI4) (GDP level 5) are in cluster 4; regions Piemonte (ITC1), Liguria (ITC3), Friuli-Venezia Giulia (ITH4), Toscana (ITI1), Marche (ITI3) (GDP level 4) are in cluster 5. All the other Italian regions (Campania (ITF3) to Sardegna (ITG2)) with GDP level 2) are in cluster 3. Italian regions are in clusters homogeneous with respect to the stage of development as measured by the level of GDP.

The regions in cluster 1 are mostly (first three) regions of France (one region FR21); the regions in cluster 2 regions of Spain (ES), France (FR) and United Kingdom (UK); regions

Table 24 Fuzzy C-Medoids RCI 2016 clusters with GDP contiguity constraint

Medoid	Basic	Efficiency	Innovation	
1 FR21 Champagne-Ardenne	0.081	− 0.118	− 0.026	
2 FR81 Languedoc-Roussillon	− 0.026	− 0.055	0.034	ITF1, ITF2 ITI2 (GDP 3)
3 HU32	− 0.986	− 0.900	− 1.098	ITF3, ITF4, ITF5 ITF6, ITG1 ITG2 (GDP 2)
4 NL11 Groningen	0.405	0.445	0.464	ITC2, ITC4, ITH1 ITH2, ITH3 ITH5, ITI4 (GDP 5)
5 UKD1 Cumbria	0.173	0.197	0.258	ITC1, ITC3, ITH4 ITI1, ITI3 (GDP 4)

Table 25 Fuzzy C-Medoids RCI 2016 with GDP constraint cluster composition

	AT	BE	BG	CZ	DE	DK	EE	EL	ES	FI	FR	HR	HU	IE
Cluster 1											1			
Cluster 2	1	4		1	5	1		1	7		12			1
Cluster 3			6	5			1	11	5			2	6	
Cluster 4	6	3		1	24	3			3	2	1			1
Cluster 5	1	2			8	1		1	4	2	8		1	
	8	9	6	7	37	5	1	13	19	4	22	2	7	2

	IT	LT	LU	LV	NL	PL	PT	RO	SE	SI	SK	UK	
Cluster 1													1
Cluster 2	3					1	1				15		53
Cluster 3	6	1		1		14	5	7		1	3	2	76
Cluster 4	7		1		6			1	3		1	7	70
Cluster 5	5				5	1	1		5	1		10	56
	21	1	1	1	11	16	7	8	8	2	4	34	256

in cluster 3 of Greece (EL), Poland (PL) and Romania (RO); the regions in cluster 4 mostly regions of Germany (DE), Italy (IT) and United Kingdom (UK) and the regions in cluster 5 mostly regions of Germany (DE), France (FR) and United Kingdom (UK) (Table 25).

The cross-table GDP level/cluster shows GDP level homogeneity under constraint on the level of GDP and coherence. The regions with GDP level 1 and 2 are in cluster 3, respectively; the regions with GDP level 3 are mostly in cluster 2, with GDP 4 mostly in cluster 5 and with GDP 5 mostly in cluster 4 (Table 26).

4.7.1 Comparison with RCI 2016 Clustering Without Constraints

The comparison with the clusters RCI 2016 without the constraint on the stage of development (Sect. 4.2) shows a slight downgrade for regions with GDP level 2 (in particular with respect to the value of the subindex Innovation), an upgrade for all the other regions.

Table 26 Fuzzy C-Medoids RCI 2016 with GDP level constraint cross table GDP/area

	GDP level 1	GDP level 2	GDP level 3	GDP level 4	GDP level 5	
Cluster 1				1		1
Cluster 2		1	43	5	4	53
Cluster 3	19	56			1	76
Cluster 4			4	6	60	70
Cluster 5			6	45	5	56
	19	57	53	57	70	256

This means that Italian regions in GDP level 2 are in clusters with regions—with the same GDP level—performing worst in the three subindexes; regions in GDP levels 3, 4 and 5 are in clusters with regions—with the same GDP level—performing better in the three subindexes.

5 Conclusions

We presented an application of the Cross Sectional and Longitudinal Fuzzy C-Medoids Clustering with *contiguity* constraints. The temporal aspect is dealt with by using appropriate measures of dissimilarity between time trajectories, in particular by distinguishing the cross-sectional and Longitudinal (variation over time) aspects of the trajectories. The *contiguity* among units is dealt with adding a *contiguity* penalization term to the objective function, depending on a suitable *contiguity* matrix.

The models are applied to the classification of the European NUTS on the basis of the observed dynamics of the Basic, Efficiency and Innovation subindexes of the Regional Competitiveness Index (RCI) 2013 and 2016. The positioning of the Italian regions is deeply analyzed. Two *contiguity* constraints, one based on the European Western, Southern, Central and Nothern geographic areas and one on the level of GDP—taken into account in the computation of the RCI—are also introduced in the models.

The application highlights the ability of the proposed models—in particular of the Cross sectional and Longitudinal Fuzzy C-Medoids Clustering with *contiguity* constraints—to use the information in the multivariate data, either temporal or based on any *contiguity* relation, allowing a deep study of the characteristics of the Italian regions at the basis of their positioning in the clustering of the European NUTS based on the the subindexes of the RCI.

Possible developments at the application level are the clustering with respect to other composite indexes (Human Development Index, Well Being) and the harmonization of the obtained partitions, besides the extension of the considered periods of time and finest regional levels (an example of application of the RCI at the level NUTS3 is in De Giovanni and Sica (2014)).

Possible developments at the methodological level are the models robust to the presence of outliers.

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