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SPATIO-TEMPORAL PATTERNS OF THE TALENTS LABOUR MARKET ACROSS EUROPEAN COUNTRIES[1]

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Biographical Notes

Cristina Lincaru, PhD is a senior researcher at National Scientific Research Institute for Labour and Social Protection (INCSMPS), Romania. Her scientific career on the long-term is aimed at exploiting the theory and practice of the new model of work based on innovation and knowledge, shaped in the theoretical framework of the New Economic Geography and Evolutionary Economy. Her specific interest is dedicated on the acquisition of new knowledge through the use of spatial econometrics instruments, the foundations of phenomena, observable facts, and specific features of local labour markets from a functional perspective. She is a member of the Council of the Romanian Regional Science Association, a member of the European Regional Science Association and Regional Science Association International, and the Romanian Statistics Society. She is a Fellow of the Regional Studies Association (FeRSA).

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Speranta Pirciog, PhD is President of Scientific Board, Deputy Director at the National Scientific Research Institute for Labour and Social Protection. Her research fields are labour economics, and regional development. She is a member of some national and international associations like like the Romanian Regional Science Association, European Regional Science Association, Regional Science Association International, Romanian Statistics Society.

Adriana Grigorescu, PhD is University Professor at National University of Political Studies and Public Administration, with over 30 years of research - interdisciplinary and/or multidisciplinary - mainly on problematic incidence between the public and private sectors. The field of management research in the public and private sector is embodied in comparative analyses, holistic, integrated managerial approaches. She has a rich experience of coordinating internships and doctoral theses in the field of Public Sector and/or Business Management, with topics mainly aimed at comparative analysis, transfer of best practices, optimization of processes in public administration.

Gabriela Tudose, PhD is a senior researcher at National Scientific Research Institute for Labour and Social Protection (INCSMPS), Romania. Her research interest is in the recent radical transformation of the economy and society in a digital and green perspective and its impact on the labour market, labour market policies. Other interests are regional studies, the research of competencies and lifelong learning and those related to the improvement of recovery and resilience policies adequate to their integrated capacity into case of overlapping crises.

Abstract

The new strategical Europe’s framework shapes the double green and digital transformation. These objectives demand highly specialised and formalised labour markets, with high human capital strongly connected to lifelong learning and highly geographically mobile, in short, demand talents. Frelak et al. (2020) point out that “EU Member States have been less successful than other OECD countries in attracting skilled migrants” (p.13) to fill the talent labour market deficit. Our research question is: are similar or dissimilar talent labour markets at NUTS 0 level? We analyse the talents, as defined by Marie Skłodowska-Curie Actions (MSCA), concerning national labour markets by two main dimensions: a) the work intensity defined by the working programme - full-time or part-time; and b) the institutional employer type - public, private, Ppivate government dependent or private government independent as well as the working relationship (working contract, freelancer, self-employed, relationship service) described by the type of the employer (public institutions, private institutions, private government dependent institutions, private government independent institutions). The education linked with the employment characteristics analysis approach shapes the roadmap towards a new paradigm shift in skills. The New 2020 European Skills Agenda launched this paradigm for sustainable competitiveness, social fairness, and resilience (COM/2020/274 final). We analyze for the period 2013-2019 the NUTS0 the spatial pattern of the students enrolled in ISCED 8: doctoral or equivalent level by type of institution and intensity of participation in knowledge and innovation economy, with Eurostat data. We apply the Spatio-temporal Analysis method called

Spatially Constrained Multivariate Clustering, one of the Similarity checks –Grouping Analysis ARC GIS tool. We evaluate the optimal number of groups - using the Calinski-Harabasz pseudo-F-statistic. Conclusion remarks point that if learning is work in a knowledge economy, then if Europe intends to attract talent has to ensure employment quality for talents: security prevails over flexibility! The successful European model to attract talent has a full-time program work intensity, and public institutional employers prevail. Our opinion is that talent employment policies must be re-designed under the job security need for talents and processes more visible post-December 2019 Covid pandemic. Further research directions are employment contract and work intensity across ERA in Covid times with new tendencies to change the transactional model with the relational model.

Keywords: Talents, Geography of knowledge, Similarity check – Grouping Analysis, Spatial statistics.
JEL Classification: O32, J 24**,** R11, C31, C33.

1. Introduction

The new strategical Europe's framework shapes the double green and digital transformation. These objectives require highly specialised and formalised labour markets, with high human capital strongly connected to lifelong learning and highly geographically mobile, increasing the demand for talents.

Frelak et al. (2020) point out that "EU Member States have been less successful than other OECD countries in attracting skilled migrants" (p.13) to fill the talent labour market deficit. The demographical dynamic for the EU is not able to ensure that the highly skilled labour force works with artificial intelligence. International students and young adults are among the most highly mobile across countries today. This talented elite often originates from developing countries. It migrates to industrial economies to achieve a higher level of carrier offers and a good standard of living for their family members. Many return home with innovative ideas, experiences, and valuable capital for national development, whilst others remain to produce quality goods and services that are useful everywhere in the global economy. Globalization's economic potential depends on the international mobility of incredibly talented individuals that transfer knowledge, new technologies, ideas, business capacities, and other creative capabilities. Developing countries and advanced economies may gain from this mobility if it is well-understood and design policies accordingly.

The tremendous importance of the topic develops a dynamic policy for education coupled with a harmonized statistical background. We remark the Regulation (EC) No 452/2008 of the European Parliament and of the Council of 23 April 2008, which marks an essential reference for knowledge economy manifestation by the new framework regarding "the production and development of statistics on education and lifelong learning" (p. 227).

According to the 1997 version of the International Standard Classification of Education (ISCED), the concept of 'education' present in Regulation (EC) No 452/2008 means organised and sustained communication designed to bring about learning.

After five years, the Council Resolution of 27 June 2002 on lifelong learning (OJ C 163, 9.7.2002, p. 1) points that 'lifelong learning' means all learning activities that are undertaken throughout life to improve knowledge, skills and competencies within a personal, civic, social and employment-related perspective. Other statistics on education and lifelong learning refers to the aspects presented in Table 1.

Table 1. The fields of statistics on education required by Regulation (EC) No 452/2008 of the European Parliament and of the Council of 23 April 2008

Statistics on education fields	Domain's perspectives required at Community level for monitoring policies
economy	education, research, competitiveness, and growth
labour market	employment policies
social inclusion	poverty, social inclusion, and migrant integration

Source: authors' synthesis from Regulation (EC) No 452/2008

Digital and green transformation launches the economies' global race for talents. On this background, our research question is: are similar or dissimilar talent labour markets at NUTS 0 across Europe?

We apply the Spatio-temporal Analysis Method called **Spatially Constrained Multivariate Clustering (SCMC),** one of the Similarity checks –Grouping Analysis ARC GIS-tool. We evaluate the optimal number of groups - using the Calinski-Harabasz pseudo-F-statistic.

Talents have become a literature topic since 2002, launched by Florida. Florida (2002) linked talents with space under the Economic Geography of Talents. Tuccio (2019) compares how OECD countries fare in attracting talented migrants. Talents are defined by three criteria: high level of education (workers with master's or doctorate degrees), entrepreneurs and university students. The study's main conclusion is that the OECD countries offer a significant heterogeneity of talent attractiveness. Moretti (2012) presents another geographical approach for talents under the name of creative people. Next to the spatial distribution of talents toward urban agglomeration, there is talent mobility in the open migration chains (Kuznetsov & Sabel (2006), followed by Solimano (2008)), which envisages the international mobility of talents. The importance of the roles of talents, especially in the knowledge economy, is emphasized by Charan et al. (2018). Also, Towers Watson (2014) shows that employers find it challenging to get and keep key talent, including top performers and high-potential employees. Cui et al. (2019) explore the spatial migration patterns of highly educated human capital. In China, "little is known about the migration of these elite university graduates and its underlying driving force" (p. 397). The Covid crisis strengthened Europe's interest in developing a talent attraction policy. The impact of Covid-19 on talent attraction could provide an unexpected opportunity for the EU on the background of temporary interruption of mobility. Concerning talents' Spatio-temporal analysis, Lincaru et al. (2021) identified patterns of the talent labour market across European countries before the Covid crisis. In the same register, Xu Huang (2019) proposed the analysis and prediction of the spatial-temporal talent mobility patterns model, which combines convolution and recurrent neural networks to forecast regional talent flows.

Tuccio (2019) classifies talent attraction factors into pecuniary, nonpecuniary and mixed factors. Meister (2021), starting from Workplace 2021 HR Sentiment Survey that found that 68% of senior HR leaders (of which 40% were CHROs) rated employee well-being and mental health as a top priority, concludes that "the pandemic has given employers increased visibility into the life struggles of their employees and has shifted the focus from just organizational issues to individual human life experiences" (p.6).

The 2014 Global Talent Management and Rewards Study explores the disconnect between employer and employee views on attracting and retaining a productive workforce. Even if employers and employees agree on base payment, career advancement opportunities, learning opportunities and the organization's reputation, job security is the critical driver that differentiates its importance for the following aspects: employees are the second attraction driver and the fourth retention driver; employers are only the seventh attraction driver but are not viewed as retention driver (Towers Watson, 2014).

The importance of the well-being at the destination location is an attraction driver regardless of economic system and level of development. Cui et al. (2019) found a failure of the current policy to attract talent in less developed cities, while "the elite graduates were found aggregating in eastern first-tier cities" (p. 397). The elite's mobility trajectories also depend on the university's location. These conclusions are highly relevant in terms of talent policy attraction for "promoting regional development in the knowledge era" (p. 399), even though human capital is the key driver for innovation.

April 2021 starts the "Great Attrition or Great Resignation" (counts over 11 million jobs) in the USA and "underscores the many ways the pandemic has irrevocably changed what people expect from work" (de Smet et al., 2021, p.3) from transaction toward human relationship. Also, a structural gap in the labour supply shortage emerges, regardless of the migrants & automatization substitution effect (de Smet et al., 2022). In 2021 "two out of five employees plan to leave in the next three to six months for new reasons like reshuffling, reinventing and reassessing". (de Smet et al., 2022, p. 3).

Sánchez-Moral et al. (2018) distinguish between the attraction and retaining of talents based on a longitudinal micro-database from the Spanish Social Security Office in the case of Madrid.

Beyond the agglomeration effect, authors identify the "escalator regions effect". The escalator model propels the "careers of young creative workers that had been attracted to them" (p. 789) but fails to retain them.

Hauswald et al. (2016) suggest family firms as a long-term employment relationship model. Family businesses project the image of "trustworthiness, security, and stability" (p. 963) based on relationships, not transactions. They point out that the family model works better in more hostile economic environments, the image associated with inflexibility and resistance to change.

2. Data and Method

Our definition of talents aligns with the Marie Skłodowska-Curie Actions (MSCA), a vital part of the Excellence pillar of Horizon 2020: talents are persons with a doctoral or equivalent level (ISCED 8) equal to EQF 8. Talents consequently detain "knowledge at the most advanced frontier of a field of work or study and the interface between fields" (EQF, 2008, p. 9).

Data

Methodological notes regarding the indicator measurement

With regard to tertiary education OECD (2003) points out that "in most instances the definition is derived from statistical standards developed by international organisations such as the IMF, OECD, Eurostat, ILO" (p. 1). The standards of international statistics on education and training systems are set by the three international organisations jointly administering the annual UOE data collection:

1) The United Nations Educational, Scientific, and Cultural Organization Institute for Statistics (UNESCO-UIS);
2) The Organization for Economic Co-operation and Development (OECD);
3) The Statistical Office of the European Union (EUROSTAT).

In our paper we use the Eurostat Education concepts for tertiary education measurement according to UOE harmonized data collection (see Box1).

Box 1. Tertiary education concepts according to Eurostat Education Measurement Methodology

Full-time, students: Since the theoretical and actual duration of education programmes differs widely between programmes and countries, and since there are no internationally accepted norms, relative national norms are applied to establish full-time participation.
At the tertiary level, an individual is considered full-time (when head-count data are reported) if he/she is taking a course-load/educational programme considered to require at least **75 per cent of a full-time commitment of time and resources**. Additionally, it is expected that the student has remained in the programme for the entire academic year.

Full-time equivalents students: A full-time equivalent (FTE) measure attempts to standardise a student's actual load against the normal load. Calculating the full-time / part-time status requires information on the time periods for actual and normal loads. National norms are applied for this purpose.
Where data and norms on individual participation are available (e.g. "credentials"), the product of the fraction of the normal course load for a full-time student and the fraction of the school / academic year is used as a measure of course-load.

$$FTE = \frac{\text{actual study load}}{\text{normal study load}} * \frac{\text{actual duration of study during reference period}}{\text{normal duration of study during reference period}} \quad (1)$$

If equivalent programmes exist separately as full-time and part-time programmes, then the ratio of the theoretical durations of these programmes can be used as a proxy for the conversion factors of part-time data into full-time equivalents.
When actual study load information is not available**, a full-time student is considered equal to one.**

FTE and part-time students are estimated to FTEs according to best knowledge in the country. If no information for estimation is available**, one part-time student is considered 0.5 FTE.**
Students: A student is defined as any individual participating in educational services covered by the data collection. The number of students enrolled refers to the count of students studying in the reference period, the school/academic year. Double-counting should be avoided.

Source: https://ec.europa.eu/eurostat/cache/metadata/Annexes/educ_uoe_enr_esms_an1.htm

Indicator & variables

Indicator: Students enrolled in tertiary education by education level, programme orientation, sex, type of institution and intensity of participation [educ_uoe_enrt01]

Space: 37 countries, NUTS 0

Time - 7 years, between 2013 and 2019. As there are less than the minimum number of terms, we do not apply space-time cube analysis.

Variables: TpI8e, PpI8e, RpI8e, SPTpI8, T1pI8e, T2pI8e, SI8_T2, FpI8e - generate different spatio-temporal patterns (see Table 2 for descriptions and labels)

Table 2. The variables of the model

Variable name	Description	Short label
TpI8e	the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education (levels 5-8)	share of doctoral in tertiary
PpI8e	the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education in **private** institutions	share of doctoral in private tertiary
RpI8e	the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education in **public** institutions	share of doctoral in public tertiary

SPTpI8	the share of Students enrolled in Doctoral or equivalent level (level 8) from **public** institution in total students enrolled in doctoral or equivalent level (level 8)	share of doctoral from **public** in total doctoral
T1pI8e	the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education (levels 5-8) in **part time** programmes	share of doctoral in part time tertiary
T2pI8e	the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education (levels 5-8) in **full time** programmes	share of doctoral in full time tertiary
SI8_T2	the share of Students enrolled in Doctoral or equivalent level (level 8) full **time** in total Students enrolled in Doctoral or equivalent level (level 8)	share of doctoral from **full time** in total doctoral
FpI8e	the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education (levels 5-8) in **full time equivalents** programmes	share of doctoral in full time equivalents tertiary

Source: Own representation.

Methodological notes: 1. There are some specific distinctions with regard to private educational institutions concepts. "An institution is classified as private if ultimate control rests with a non-governmental organization (e.g. a church, trade union or business enterprise), or if its governing board consists mostly of members not selected by a public agency" (OECD, 2002).
2. OECD (2002) also makes the distinction between dependent and independent private institution: "A government-dependent private institution is an institution that receives more than 50% per cent of its core funding from government agencies. An independent private institution is an institution that receives less than 50% per cent of its core funding from government agencies" (OECD, 2002).
3. "Core funding" refers to the funds that support the basic educational services of the institutions. It does not include funds provided specifically for research projects, payments for services purchased or contracted by private organizations, or fees and subsidies received for ancillary services, such as lodging and meals.(OECD, 2003)

Method

Recently, the New 2020 European Skills Agenda launched the paradigm of sustainable competitiveness, social fairness, and resilience (COM/2020/274 final). On this background, education and employment characteristics link together and the new approach shapes the roadmap towards a new paradigm shift on skills. In order to reflect these new approaches, talent analysis envisages two main dimensions, namely:

a) **the work intensity** defined by the working programme: full time or part-time. This dimension profile the work relations described by the following typology: working contract, freelancer, self-employed, relationship service, etc.;

[2] https://ec.europa.eu/eurostat/cache/metadata/Annexes/educ_uoe_enr_esms_an1.htm

b) the institutional employer types. The type of the employer according to (OECD, 2003 and OECD, 2002) points to following typology: public institutions, private institutions, private government dependant institutions, private government independent institutions.

In our research we use the Spatio-temporal Analysis Method called **Spatially Constrained Multivariate Clustering (SCMC)**, one of the Similarity checks –Grouping Analysis ARC GIS-tool. We evaluate the optimal "n" number of groups - using the Calinski-Harabasz pseudo-F-statistic. The Software used is Arc Gis Pro 2.8. The largest F-statistic, indicating how many clusters will be most effective at distinguishing the features and variables you specified.the K-means solution has the highest Calinski-Harabasz score. K Nearest Neighbours algorithm is a supervised machine learning algorithm used to solve the classification problem (details in Box 2).

Box 2. Multivariate Clustering Tool (MCT)

MCT uses "unsupervised machine learning methods to determine natural clusters in data". Unsupervised method means that "is not required a set of pre-classified features to guide or train the method to find the clusters in data" (ESRI ArcGis Pro, 2020).
It is a NP-hard clustering analysis algorithm type that find "a solution will perfectly maximize both within-group similarities and between-group differences" (ESRI ArcGis Pro, 2020)
It provides useful input for any type of decision makers from business but also from public administration.

„R^2=(TSS - ESS) / TSS (2)

where:

TSS is the total sum of squares. TSS is calculated by squaring and then summing deviations from the global mean value for a variable.

ESS is the explained sum of squares. ESS is calculated the same way, except deviations are cluster by cluster: every value is subtracted from the mean value for the cluster it belongs to and is then squared and summed." (ESRI ArcGis Pro, 2020)

Algorithm to calculate the number of clusters in MCT

The clustering effectiveness is measured using the Calinski-Harabasz pseudo F-statistic, which is a ratio of between-cluster variance to within-cluster variance. In other words, a ratio reflecting within-group similarity and between-group difference:

$$F=\frac{\frac{R^2}{n_c-1}}{\frac{1-R^2}{n-n_c}} \quad (3)$$

where:

$$R^2 = \frac{SST-SSE}{SST} \quad (4)$$

and SST reflects between-cluster differences and SSE reflects within-cluster similarity:

$$SST=\sum_{i=1}^{n_c}\sum_{j=1}^{n_t}\sum_{k=1}^{n_v}\left(V_{ij}^k - \overline{V^k}\right)^2 \quad (5)$$

$$SSE=\sum_{i=1}^{n_c}\sum_{j=1}^{n_t}\sum_{k=1}^{n_v}\left(V_{ij}^k - \overline{V_t^k}\right)^2 \quad (6)$$

where:

n= the number of features

n_i = the number of features in cluster i

n_c = the number of classes (clusters)
n_v = the number of variables used to cluster features
V_{ij}^k = the value of kth variable of the jth feature in ith cluster
$\overline{V^k}$= the mean value of the kth variable
$\overline{V_t^k}$= the mean value of the kth variable in cluster i

Clustering Method
The MCT uses the K Means algorithm by default. The goal of the K Means algorithm is to partition features so the differences among the features in a cluster, over all clusters, are minimized. Because the algorithm is NP-hard, a greedy heuristic is employed to cluster features. The greedy algorithm will always converge to a local minimum but will not always find the global (most optimal) minimum. The **K Means algorithm works** by first identifying seeds used to grow each cluster. Consequently, the number of seeds will always match the Number of Clusters. The first seed is selected randomly. Selection of remaining seeds, however, while still employing a random component, applies a weighting that favours selection of subsequent seeds farthest in data space from the existing set of seed features (this part of the algorithm is called **K Means ++).** Because of the random component in finding seeds whenever you select **Optimized seed locations** or **Random seed locations** for the **Initialization Method**, you might get variations in clustering results from one run of the tool to the next.

Once the seeds are identified, all features are assigned to the closest seed feature (closest in data space). For each cluster of features, a mean data centre is computed, and each feature is reassigned to the closest centre. The process of computing a mean data centre for each cluster and then reassigning features to the closest centre continues until cluster membership stabilizes (up to a maximum of 100 iterations).
Source: (ESRI ArcGis Pro, 2020)

Spatial relationship management

The spatial constraint uses spatial relationships' conceptualisation by spatially constrained matrix, with **distance threshold method**. We generate the Spatial Weights Matrix in Arc Map 10.2.2. GIS Tool. The tool running result is a Spatial Weights Matrix with the following characteristics:

(1) The distance criteria are approx. 1350 km as a result of the default neighbourhood search threshold.

(2) Number of Features: 37

(3) Percentage of Spatial Connectivity: 44.7

(4) Average number of neighbours: 16.54

(5) Minimum number of neighbours: 1

(6) Maximum number of neighbours: 26

We find the number of groups of 5 clusters retained as the first local maximum of the Pseudo-F statistics.

Limits for the model

The fixed distance method defines the conceptualisation of spatial relationship. This way of defining neighbours induces the following limits for the model:

(1) Insularization effect.

(2) Not all countries have data.

(3) The missing are managed to be filled with „0”.

3. Results and Discussion

Talent intensity and attraction tendency

The clusters built on **SMSC** for the share of students enrolled in Doctoral of Equivalent for ISCED 8 level in total students enrolled in Tertiary Education (ISCED level 5-8) during 2013-2019 period (with spatial constraint built on spatial weight matrix) is illustrate in Figure 1. Countries are clustered in groups coded as G followed by an identification number and represented by a unique color.

Central and partially Northern Europe present in the Mauve Cluster G5 show the highest concentration of talents. Mainly in Western and Eastern part of Europe it is the Orange Cluster G4 that gathers the average values. Remarkably, the clustering tendency in the Southern part of Europe in Blue Cluster G1 is described by the lowest values with regard to the talent attraction capacity. Red Cluster G2 - Liechtenstein and Green Cluster G3 - Luxembourg are outliers.

General tendency for the period 2013-2019 is of convergence of G4 towards G5, but still under North - South polarization pattern. The standardized values (Figure 1) confirm the already announced convergence tendency:

In the year 2013: $G5= 2 * G4 = 5.5*G1$ (7)

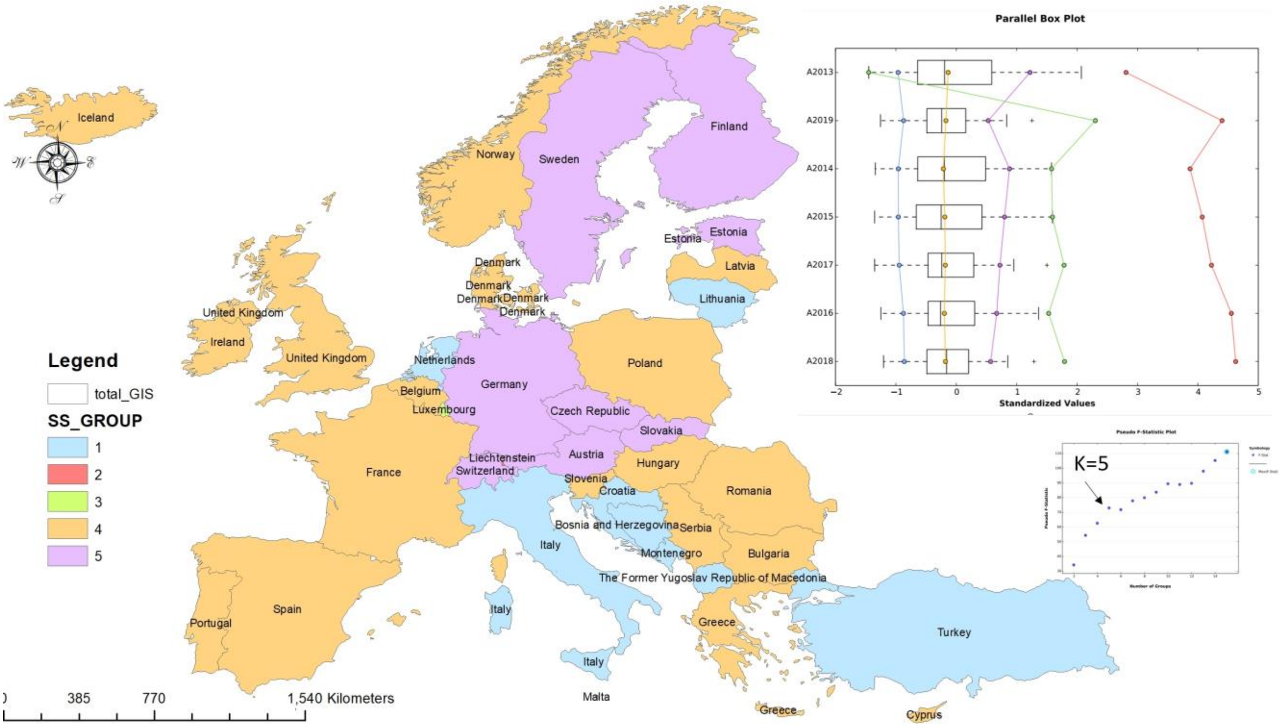
In the year 2019: $G5= 1,6* G4 = 4,7*G1$ (8)

Looking at the Annex1, the Mean TpI8e confirms the convergence of G5 and G1 towards G4 for the period 2013-2019:

G5 A2013 6.16% ↘ A2019 5.78%
G4 A2013 3.03% ↗ A2019 3.51%
G1 A2013 1.12% ↗ A2019 1.24%

Both Paralel Box Plot and Group statistic by year (selection in Anex 1) indicate that in the year 2018 (codified A2018) $R2$ =0,93; the largest $R2$ is for the TpI8e variable, the best discriminant compared with other years.

Figure 1. The clusters built on Spatial Statistics Grouping Analysis for the share of students enrolled in Doctoral of Equivalent for ISCED 8 level in total students enrolled in Tertiary Education (ISCED level 5-8) during 2013-2019 period (with spatial constraint built on spatial weight matrix)



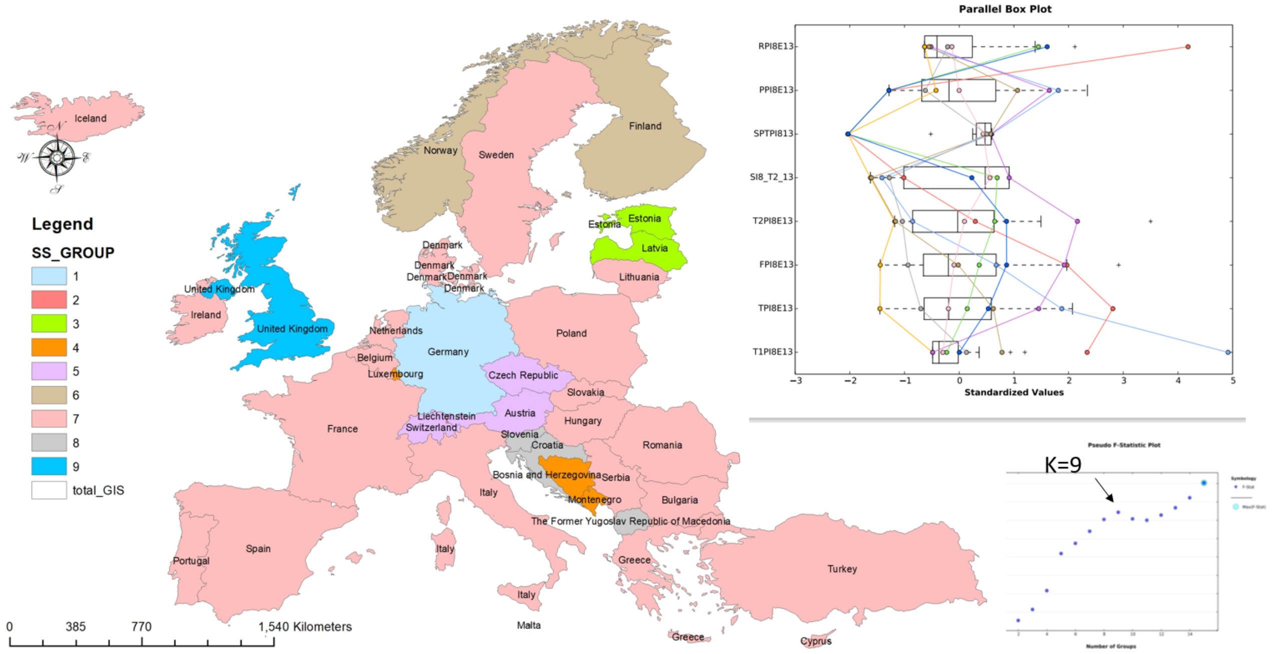
Source: own processing using Arc Map 10.2.2

The G5 is the leader cluster in view to concentrate talents double than G4 and 4 times higher than G1. On long term the tendency is to converge towards G4 (close to the mean level 0 talent concentration). This fact confirms the ERA – **European Research Area** functioning. As we noticed, 2018 marks a shock presence, fact confirmed by (Jones, 2018). Locally, under the crisis effect, the convergence tendency with regard to the intensity of talent attraction stops.

Talents labour market models – work intensity & institutional employer

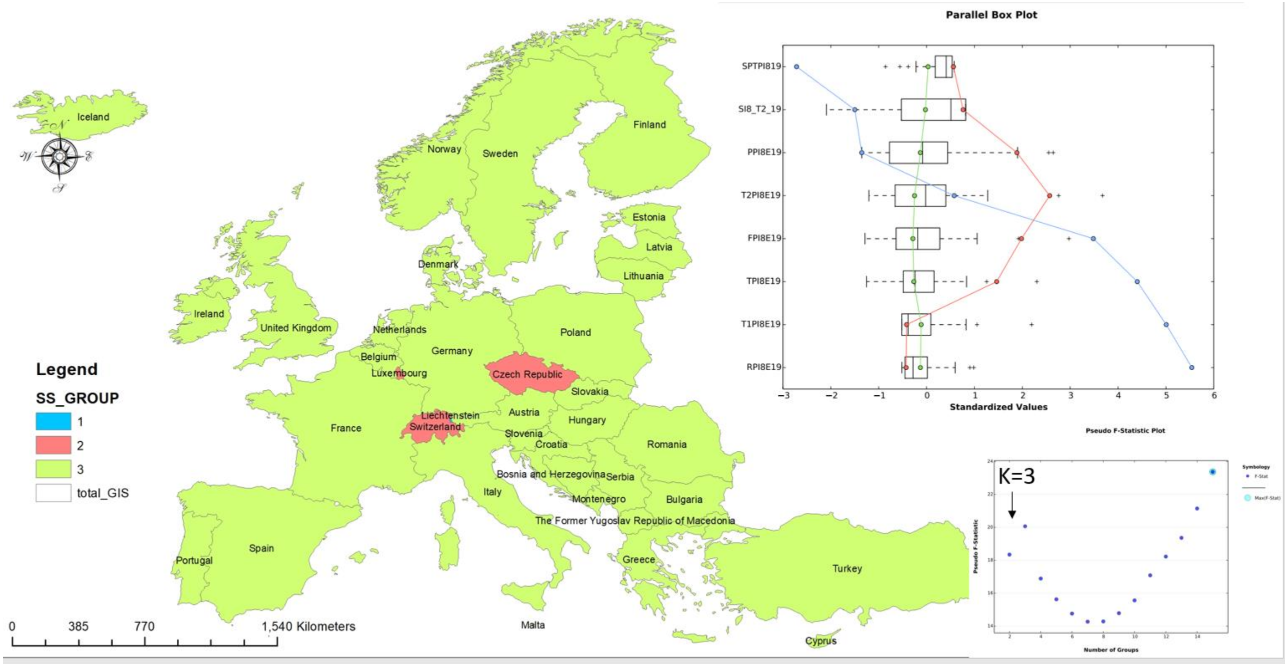
Running the multivariate analysis model for all 8 variables generated in Table 2, result the Figure 2 for 2013 and Figure 3 for 2018 patterns. The spatial heterogeneity of talents spatial distribution and the blend of education and employment tend to decrease from 2013 to 2018. If in 2013 the K-means solution has the highest Calinski-Harabasz score producing 9 clusters, in 2018 result only 3 clusters.

Figure 2. The 2013 clusters built on Spatial Statistics Grouping Analysis for the share TpI8e, Ppl8e, SPTpl8, T1pl8e, T2pl8e, SI8_T2, Fpl8e (with spatial constraint built on spatial weight matrix)



Source: own processing using Arc Map 10.2.2

Figure 3. The 2018 clusters built on Spatial Statistics Grouping Analysis for the share TpI8e, Ppl8e, SPTpl8, T1pl8e, T2pl8e, SI8_T2, Fpl8e (with spatial constraint built on spatial weight matrix)

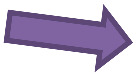
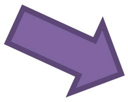
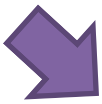
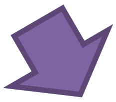


Source: own processing using Arc Map 10.2.2

The R^2 value reflects how much of the variation in the original TestScores data was retained after the clustering process, so the larger the R^2 value is for a particular variable, the better that variable is at discriminating among your features (Table 3).

Table 3. Comparing Data – Variables Hierarchy by their discriminant power for the multivariate cluster analysis in 2013 and 2019

Variable	short label	R2 2013	*Mean*		R2 2019	*Mean*	*dMean*	Gr. rate	
RpI8e	share of doctoral in public tertiary	0.75	***1.29***		0.86	***1.56***	***0.2754***	0.21	**Increases polarisaion**
TpI8e	share of doctoral in tertiary	0.75	***3.34***		0.76	***4.07***	***0.7261***	0.22	
FpI8e	share of doctoral in full time equivalents tertiary	0.71	***3.05***		0.72	***3.76***	***0.7136***	0.23	
T1pI8e	share of doctoral in part time tertiary	0.93	***4.38***		0.7	***5.55***	***1.1716***	0.27	**creases**

T2pI8e	share of doctoral in full time tertiary	**0.75**	***2.68***		**0.6**	***3.35***	***0.675***	0.25	
PpI8e	share of doctoral in private tertiary	**0.6**	***3.45***		**0.35**	***4***	***0.5489***	0.16	
SPTpI8	share of doctoral from **public** in total doctoral	**0.97**	***77.4***		**0.23**	***82.5***	***5.1093***	0.07	
SI8_T2	share of doctoral from **full time** in total doctoral	**0.88**	***64***		**0.11**	***71.9***	***7.9399***	0.12	

Source: Own representation.

The following variables increase their contribution at discriminating among features with R2 higher than 0.72. Exceptions are Switzerland, Czech Republic and Luxembourg, countries in the Cluster Red in the 2018 model:

(1) **RpI8e -** the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education in public institutions, which presents the lowest variability (see Parallel Box Plot in Figure 3).

(2) **TpI8e -** the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education (levels 5-8).

(3) **FpI8e -** the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education (levels 5-8) in programmes full time equivalents.

In 2018 the European Countries "are **more similar** in regard the characteristics of talent's labor markets at NUTS 0 across Europe' by the following variables:

(1) **RpI8e** - the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education in **public** institutions.

(2) **T1pI8e** - the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education (levels 5-8) in programmes **part time.**

(3) **SPTpI8** the share of Students enrolled in Doctoral or equivalent level (level 8) from **public** institution in total Students enrolled in Doctoral or equivalent level (level 8).

In 2018 the European countries are **more dissimilar** in regard the characteristics of talent labour markets at NUTS 0 across Europe for the following variables:

(1) **SI8_T2 -**the share of Students enrolled in Doctoral or equivalent level (level 8) full **time** in total Students enrolled in Doctoral or equivalent level (level 8).

(2) **PpI8e -** the share of Students enrolled in Doctoral or equivalent level (level 8) in total tertiary education in **private** institutions.

While the mean of share of doctoral from **public** in total doctoral is 82% in 2019, increasing from 77.45, it does not differentiate anymore the talent labour markets (Table 3). The other characteristic of interest is the share of doctoral from **full time** in total doctoral. This variable increases also from 64% in 2013 to 71.9% in 2019.

4. Conclusion

Conclusion and insights identify some optimal structures - part-time/full-time and institutional employer type quality of talent employment increases the capacity to adapt to the knowledge society. The statistics on education, training and lifelong learning that are of the highest importance as a basis for political decisions are included in the results. (Regulation (EC) No 452/2008).

Our main results indicate that the intensity of talent attraction (TpI8e) in 2013, 2014, 2015, 2016, 2017, 2018 and 2019 for ERA shaped a North-South pattern, where the North had a high intensity of talents and the South had a low intensity of talents, but with the general tendency of convergence towards the present time. The G5 is the leader cluster around Germany and Sweden, concentrating talents double than Western (France and Spain) and Eastern sides G4 and four times higher than G1, the Southern European Area (South of Italy and Greece mainly). In the long term, the tendency is to converge towards G4 (close to the mean level of talent concentration). This fact confirms the ERA – European Research Area functioning. Locally, under the crisis effect, the convergence tendency regarding the intensity of talent attraction stops. Our analysis presents the limit given by the data, so that we evaluate only attraction and not retained in the sense of Sánchez-Moral et al. (2018).

More than ever, the increasing demand for the knowledge economy changes the cognitive content of work (Ciucă et al., 2019), and talents transform learning in work. “Yes” is the answer to the research question whether there are "similar or dissimilar talent's labour markets at NUTS 0 across Europe". Our model indicates a convergence tendency towards a similar European model where the full-time programme defines work intensity as a share of doctoral in full-time equivalent tertiary and the institutional employer is public tertiary. In other words, Europe must attract talent in private / businesses intended to develop Knowledge Economy.

Conclusion remarks highlight that if learning is work in a knowledge economy, then if Europe intends to attract talent, it has to ensure employment quality for talents: **security prevails over flexibility**! The successful European model to attract talent has a full-time programme, work intensity and public institutional employers. In other words, this means that on ERA for 2013-2019 talent labour market is a transaction model and wellbeing is still predominant over the relation model and family business. The talent flows from developing countries toward developed countries if the relation model is specific for the former and the transaction model for the latter.

Covid-19 pandemic sharply diminished the geographical mobility of talents, changed the expectations of work for people and shaped a structural gap in the labour supply shortage (de Smet et al., 2021). Locations that succeed in attracting talents prove to offer job security. (Towers Watson, 2014).

Employment policies must drive the new digital and green transformation but be more tuned with the talent's job security needs. The new complex paradigm put a new light on the perception of job security, increasing demand for talent attracting, the fact that opens new future research areas relevant to retaining talents too: the new work perception (de Smet et al., 2021), which becomes more visible post-Covid, the new value of job security and longtime perspective of career building and control not only in the organization but autonomous, enabling workers to directly contribute to the organization and society performance, in line with Towers Watson (2014).

Sustainable regional development is wholly dependent on talent to fill the gaps. The policy to attract talent in less developed regions, on the background of talent shortage, needs to look through spatial glasses both towards the universities location and target locations when designing public policies (Cui et al., 2019). Another improvement in attracting and retaining talent is to exploit in policies the relation model (Hauswald et al., 2016) against the transaction on talent labour markets, especially in developing countries/ less developed regions.

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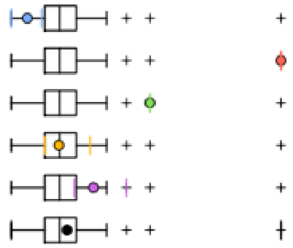
Annex 1. The statistics of clusters built on Spatial Statistics Grouping Analysis for the share of students enrolled in Doctoral of Equivalent for ISCED 8 level in total students enrolled in Tertiary Education

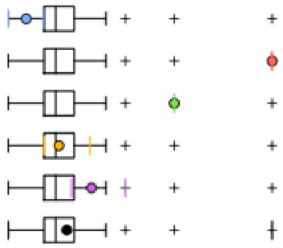
A2018: R2 = 0.93

Group	Mean	Std. Dev.	Min	Max	Share
1	1.3211	0.6447	0.2182	2.3189	0.1122
2	18.9412	0.0000	18.9412	18.9412	0.0000
3	9.8396	0.0000	9.8396	9.8396	0.0000
4	3.5115	0.7953	2.5240	5.6789	0.1685
5	5.9128	1.1821	4.5659	8.2183	0.1951
Total	4.0859	3.2111	0.2182	18.9412	1.0000



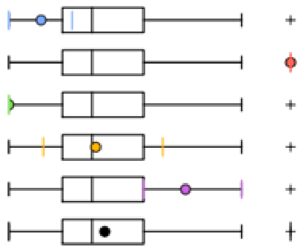
A2019: R2 = 0.93

Group	Mean	Std. Dev.	Min	Max	Share
1	1.2408	0.7509	0.0000	2.4336	0.1328
2	18.3315	0.0000	18.3315	18.3315	0.0000
3	11.5320	0.0000	11.5320	11.5320	0.0000
4	3.5146	0.8199	2.4913	5.6687	0.1733
5	5.7839	1.1943	4.4016	8.1382	0.2038
Total	4.0693	3.2414	0.0000	18.3315	1.0000



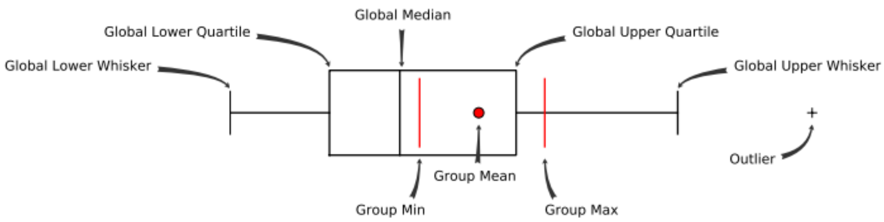
A2013: R2 = 0.83

Group	Mean	Std. Dev.	Min	Max	Share
1	1.1183	0.8133	0.0000	2.2063	0.2246
2	9.8225	0.0000	9.8225	9.8225	0.0000
3	0.0000	0.0000	0.0000	0.0000	0.0000
4	3.0302	0.9705	1.2009	5.3620	0.4236
5	6.1582	1.1714	4.6971	8.1186	0.3483
Total	3.3432	2.3060	0.0000	9.8225	1.0000



Annex 2.

Group-Wise Summary



Overall Variable Statistics: Count = 37, Std. Distance = 55.7403, SSD = 61.2045

Variable	Mean	Std. Dev.	Min	Max	R2
SPTPI813	77.3562	38.0327	0.0000	100.0000	0.9679
T1PI8E13	4.3804	9.0297	0.0000	48.7670	0.9253
SI8_T2_13	63.9801	39.4037	0.0000	100.0000	0.8776
TPI8E13	3.3432	2.3060	0.0000	9.8225	0.7545
RPI8E13	1.2892	2.0390	0.0000	9.8225	0.7525
T2PI8E13	2.6768	2.2693	0.0000	10.6210	0.7518
FPI8E13	3.0466	2.1111	0.0000	9.2027	0.7117
PPI8E13	3.4506	2.6878	0.0000	9.7509	0.6044