Labour market attractiveness in the EU

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2018 edition

STATISTICAL
WORKING PAPERS

eurostat

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2018 edition

Manuscript completed in January 2018

Luxembourg: Publications Office of the European Union, 2018

ISBN 978-92-79-80731-2 ISSN 2315-0807 doi: 10.2785/252238 KS-TC-18-002-EN-N

Abstract

In this work we present a data product developed for the European Big Data Hackathon, a competition between 22 teams which took place in March 2017. This data product is divided in two parts: an exploration part, which is aimed to better understand the EU global labour market and to capture its heterogeneity; and an inferential part, whose goal is to establish associations between characteristics of the EU labour market and indicators designed to capture important aspects of the labour market (i.e. Skills mismatch, Mobility and Emigration). For the exploration part, we developed the concept of Labour Market Attractiveness, which consists of a combination of variables from 6 Eurostats datasets on different subjects (i.e. demographics; earnings structure; education and training; life conditions; employment and unemployment; and national accounts). Using data mining techniques, such as social networks and clustering analysis, we showed that this combined set consistently captured the country-level heterogeneity in the EU, forming well-defined clusters. For the inferential part, we used model selection analysis and weighted network correlation analyses to establish associations between the characteristics of the EU labour market and the labour market indicators. Using model selection, we showed that the Labour Market Attractiveness set was able to capture well the variations of these indicators across EU. We further showed that the Labour Market Attractiveness set can be summarized by 6 Eigenvariables (i.e. 'Unemployment', 'Poverty', 'Ageing Population', 'Education (Employed Adults)', 'Employment' and 'Earnings structure'), whose association with labour market indicators was also assessed. We argue that the combination of both exploration and inferential parts can shed some light on the complex dynamics of the EU labour market. In fact, the final goal of our developed product is to help setting effective policies to tackle typical problems of a fast-changing global labour market environment.

Key-words: Labour Market Attractiveness, Labour Market Mobility, Emigration, Skills Demand, Skills Supply.

Acknowledgements:

This work has been carried out by Joao Sollari Lopes*, Sonia Quaresma† and Marco Moura‡ for the 'European Big Data Hackathon 2017' competition and the follow-up meeting 'From Prototype to Production' organized by Eurostat Task Force 'Big Data' and Cedefop.

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1. Introduction and context

The European Big Data Hackathon took place in March 2017 — in parallel with the conference New Techniques and Technologies for Statistics. This event was organised by Eurostat and gathered 22 teams from 21 European countries. The aim was to compete for the best data product combining official statistics and Big Data to support policy makers in a pressing policy question, namely, 'How to tackle the mismatch between jobs and skills at regional level in Europe?'. Indeed, the mismatch between the available skills of the labour force and the skills required by the labour market entail significant economic and social costs for individuals and firms. Furthermore, a strong education and an efficient development of skills are essential for thriving in the emerging new economy and fast-changing labour market ([1]). Nonetheless, a survey from 2014 showed that skills mismatch (i.e. over-qualification, under-qualification) remains at 45% in the European Union (EU) (CEDEFOP, 2015). This led to the publication of the EU Guidelines for the employment policies of the Member States in 2015, which called for enhancing labour supply, skills and competences ([2]).

Our data product entailed two parts: an exploration part, in which we aimed to better understand the EU global labour market and to capture its heterogeneity; and a inferential part, where we established associations between characteristics of the EU labour market and indicators designed to capture important aspects of the labour market, such as Mobility, Emigration and the previously mentioned Skills mismatch.

For the first exploration part, we developed the concept of Labour Market Attractiveness. This concept has to be taken carefully and our approach should be seen as a first-step towards a more mature definition. We considered 17 variables from 6 Eurostat datasets with information on demography, earnings structure, education and training, life conditions, employment and unemployment, and national accounts ([3]). These variables were broken by several categorical levels (e.g. 'age groups', 'level of education', 'qualifications', 'occupations') originating more than 70 variables. Data mining techniques were then considered to analyse the compiled Labour Market Attractiveness set: distances between regions were calculated and visualized using networks; the regions were clustered using these distance; and the clusters were characterized using over-representation analysis.

For the second inferential part, we considered the characteristics of the EU labour market extracted from the first exploration part and studied their association with specific indicators designed to capture different aspects of the labour market. These indicators were developed using Eurostat datasets and comprised of Skills mismatch, Mobility and Emigration at country-level. The levels of association were studied using model selection on multivariate linear regression analyses. We further constructed Eigenvariables from the considered Labour Market Attractiveness set and performed weighted correlation network analysis on the labour market indicators.

We argue that the combination of the exploration and association studies can be invaluable to fully understand the influences on the complex dynamics of the EU labour market. Indeed, the final goal is to use this understanding to help setting policies to tackle such problems as localized excess or deficit of available labour force and/or of specific labour skills, typical problems of the fast-changing EU labour market.

([1]) https://ec.europa.eu/commission/publications/skills-education-and-lifelong-learning-european-pillar-social-rights_en

([2]) Council Decision (EU) 2015/1848 of 5 October 2015

([3]) http://ec.europa.eu/eurostat/data/database

2. Material and methods

2.1. Databases

For the construction of the Labour Market Attractiveness set, we considered 6 Eurostat datasets to capture different aspects of the attractiveness of a labour market. Thus, we chose reg_demo for Demographics data, earn for Earnings structure data, edtr for data on Education and training, ilc for Life conditions information, employ for Employment and unemployment data, and na10 for National accounts data. These main datasets comprised of 17 smaller datasets described in Annex 1. Except for two datasets, all of them refer to the year 2014. The exceptions were educ_uoe_fine06 (i.e. Total public expenditure on education) and nama_10r_2hhinc (i.e. Income of households), which referred to 2013 in order to obtain a more complete dataset.

For the construction of the Labour Market indicators in study, we also considered several Eurostat datasets (see Annex 2). To study Mobility and Emigration, we used the datasets lfso_14leeow on Labour Force and migr_emi2 on Emigration, respectively. For the construction of the Skills mismatch indicator, we assumed two major simplifications, however, these simplifications do not affect our product in terms of proof-of-concept and can be dropped in later developments. The first one was to use previously cleaned and treated data on job vacancies and education attainment from the Eurostat's labour and edtr datasets, respectively. Instead, a better approach would be to use freshly collected job portals data, but the use of this data would have two caveats: a) the cleaning and structuring of the data would require a considerable expertise on the subject; b) the normalizing of the data, using for example marginal calibration techniques, would require detailed demographic data and, more importantly, well-defined populations. The second simplification was to use an *ad hoc* mapping between qualifications (classified using ISCED-F 13) and the cross between occupations (defined using ISCO-08) and economic activity (defined using NACE Rev. 2). Nevertheless, a formal mapping system is scheduled to be released soon by European Skills, Qualifications and Occupations (ESCO) from the European Commission.

2.2. Variables considered

For each of the 17 Eurostat datasets composing Labour Market Attractiveness set, we extracted one variable. These 17 main variables were broken by several categorical levels [i.e. type of contract, age groups, level of education (ISCED 11), economic activity (NACE Rev. 2) and occupation title (ISCO-08), see Annex 7 for a full description] originating 76 variables. The entire set of these variables compose the Labour Market Attractiveness set (Table 1 and Annex 3).

Table 1: Variables of Labour Market Attractiveness

variable	description	dataset	units
ARPR	At-risk-of-poverty rate	ilc_li41	PC_POP
AROPE	At-risk-of-poverty or social exclusion	ilc_peps11	PC_POP
earn_OC[...]_Nace[...]	Earning by ISCO-08 and NACE Rev. 2	earn_ses_hourly	MN_PPS
emp_T[...]	Employment by work contract	lfst_r_lfe2eftpt	PC_POP_YGE15
emp_Y[...]	Employment by age	lfst_r_lfe2emp	PC_POP_Y[...]
emp_Y[...]_ED[...]	Employment by age and ISCED 11	lfst_r_lfe2eedu	PC_EMP_Y[...]
emp_Y[...]_Nace[...]	Employment by age and NACE Rev. 2	lfst_r_lfe2en2	PC_EMP_Y[...]
expend_ED5-8	Public expenditure on education	educ_uoe_fine06	PC_GDP
disp_income	Disposable income	nama_10r_2hhinc	PPCS_HAB
GDP	Gross Domestic Product	nama_10r_2gdp	PPS_HAB
GVAgr	Gross Value Added growth	nama_10r_2gvagr	PCH_PRE
low_work	Very low work intensity	ilc_lvhl21	PC_POP_YLE60

mat_depriv	Severe material deprivation	ilc_mddd21	PC_POP
pop_Total	Population	demo_r_d2jan	NR
pop_Y[…]	Population by age	demo_r_d2jan	PC_POP
rooms_pp	Number of rooms per person	ilc_lvho04n	AVG
training	Participation in education and training	trng_lfse_0	PC_POP_Y25–64
unemp_Y[...]	Unemployment by age	lfst_r_lfu3pers	PC_POP_Y[…]

PC_POP, Percentage of Population; MN_PPS, Mean by group in Purchasing Power Standard; PC_POP_YGE15, Percentage of Population greater or equal than 15 years old; PC_POP_Y[...], Percentage of Population of given age group; PC_GDP, Percentage of Gross Domestic Product; PPCS_HAB, Purchasing Power Consumption Standard per inhabitant; PPS_HAB, Purchasing Power Standard per inhabitant; PCH_PRE, Percentage change on previous period; PC_POP_YLE60, Percentage of Population less or equal than 60 years old; NR, Number; AVG, Average; PC_Y25–64, Percentage of Population between 25 and 64 years old.

The Mobility indicator, or Labour market mobility, was calculated as the percentage of foreigner employees, and should reflect the attractiveness of a Labour Market to foreigners. The Emigration indicator was calculated as the percentage of emigrants in a country, and should reflect the willingness of the population to leave the country. The Skills mismatch was calculated as the Euclidean difference between the proportion of students and the proportion of job vacancies by field of education (classified using ISCED-F 13, see Annex 7). Since job vacancy information is available only by occupations (defined using ISCO-08) and economic activity (defined using NACE Rev. 2), there was the need to map fields of education to the cross between occupations and economic activities using the previously mentioned *ad hoc* mapping system. Table 2 summarizes the variables used as Labour Market indicators. Note that, due to missing data Skills mismatch had only information on 8 countries (Annex 4).

Table 2: Labour market indicators

variable	description	dataset	units
Skills mismatch	Mismatch between Jobs and Skills	educ_uoe_grad02, jvs_a_nace2	DIST
Mobility	Labour Market mobility	lfso_14leeow	PC_EMP
Emigration	Emigration rate	migr_emi2	PC_POP

DIST, Euclidean distance between Jobs and Skills; PC_EMP, Percentage of employed Population; PC_POP, Percentage of Population.

2.3. Methods

Several data mining techniques were considered to analyse the compiled Labour Market Attractiveness set and the labour market indicators: Social network analysis (SNA); Partition-around-medoids (PAM) (Reynolds et al.,1992); Over-representation analysis (ORA); Model selection using multivariate linear regression analysis (Calcagno and Mazancourt, 2010); and Weighted correlation network analysis (WCNA) (Langfelder and Horvath, 2008).

A social network was used to visualize the entire Labour Market Attractiveness set according to the similarities between the countries. These similarity values were calculated as the additive inverse of weighted Euclidean distances between countries. The distances were calculated using all the 76 variables weighted in such a way that each set of variables originated from one of the 17 main variables had a weight of one. This weighting scheme was employed to insure that there was no bias towards main variables broken in many secondary variables. Prior to the calculation of the distances, the variables were made dimensionless using a min-max transformation ([4]). Finally, the network was constructed on the similarities above 0.65 using the 'Fruchterman–Reingold' algorithm as implemented in the R package 'sna' (Butts, 2016).

The countries were clustered using a PAM analysis on the previously calculated weighted Euclidean distances. This analysis uses silhouette widths to partition data into clusters. Silhouette widths are calculated by comparing how close one element is to the remaining elements of its cluster with how close it is to the elements of the nearest neighbour cluster. A clustering analysis can then be characterized by calculating the average silhouette width of all the elements. The number of considered clusters *k* was chosen by running the analysis with all possible number of clusters (k = 2, 3, ..., $n - 1$, where *n* was the number of subjects) and examining their average silhouette width. The PAM analysis was implemented in the R package 'cluster' (Maechler et al., 2016).

In order to describe the clusters created, we performed an ORA on each variable of the Labour Market Attractiveness set. This analysis can identify which variables are over-represented in each created cluster. Before performing this analysis the variables were discretized by defining a cut-off on the 90th percentile (over-representation of the higher values) and on the 10th percentile (over-representation of the lower values). The significance of these analyses was set to p-value = 0.05 ([5]).

In order to study the relation between the Labour Market indicators and the variables of the Labour Market Attractiveness set, we fitted multivariate linear regressions using the indicators as response variables. Using heuristics from the R package 'glmulti' (Calcagno, 2013), we defined which model best predicted each indicator. The model selection was performed using an exhaustive screening when the number of models was less than 200 000 or using a genetic algorithm approach as implemented in the used R package. To assure a good coverage when running the genetic algorithm approach, two replicas were run with two sets of parameters each (1st set: popsize = 100, mutrate = 0.001, sexrate = 0.1, imm = 0.3, deltaM = 0.05, deltaB = 0.05, conseq = 5; 2nd set: popsize = 200, mutrate = 0.01, sexrate = 0.2, imm = 0.6, deltaM = 0.005, deltaB = 0.005, conseq = 10). The 100 models with the lowest AICc were stored. The maximum number of predictors for the models was chosen to be the hard threshold [i.e. maximum predictors is *m* such that $m = n - 1 - 3$, where *n* is the number of subjects]. Before performing model-choice, the dataset was pre-processed by removing variables until obtaining a set of 30 using the following steps: 1) any variable with missing data; 2) variables highly correlated among them ($\rho < 0.90$); 3) variables little correlated with the response variable. This analysis allowed us to take a multivariate approach to establish associations; however, it had two caveats: firstly we had to discard all the variables with missing data; secondly looking at a best model may overshadow other interesting models.

To study the Labour Market indicators on a reduced number of variables, WCNA was employed to extract Eigenvariables from the Labour Market Attractiveness set using the R package 'WGCNA' (Langfelder and Horvath, 2008). Eigenvariables (or Modules) are groups of variables constructed based on pairwise distances. The distances are obtained by calculating Topological Overlap Matrices using the absolute value of Spearman correlations raised to the *k* power. The value of *k* was chosen by taking the minimum value above 90% of the best scored value, where the scores were calculated as suggested by the authors of the package (Langfelder and Horvath, 2008). The groups of variables were then created using weighted networks with the following settings: minimum module size = 2, cluster splitting level = 4, dynamic tree cut method = 'hybrid', and merge cut-off height = 0.2. Eigenvariables are calculated as the first Principal Component of each grouping of variables. The Module membership of a variable can be calculated as the correlation to its belonging Eigenvariable. Similarly, the quality of a Module can be assessed by calculating the average of the Module membership of all its variables. Finally, the association between the constructed Eigenvariables and the labour market indicators can be calculated using Spearman correlations ($-0.30 < \rho < 0.30$). Before performing WCNA, the dataset was pre-processed by removing variables with more than 15% of missing data.

All the analysis (including the *ad hoc* mapping system for constructing the Skills mismatch indicator) can be reproduced using R scripts stored in a github repository ([6]).

([4]) min-max transformation: $z_i = (x_i - \min(x))/(\max(x) - \min(x))$, where *z* is the transformed variable that ranges from 0 to 1.

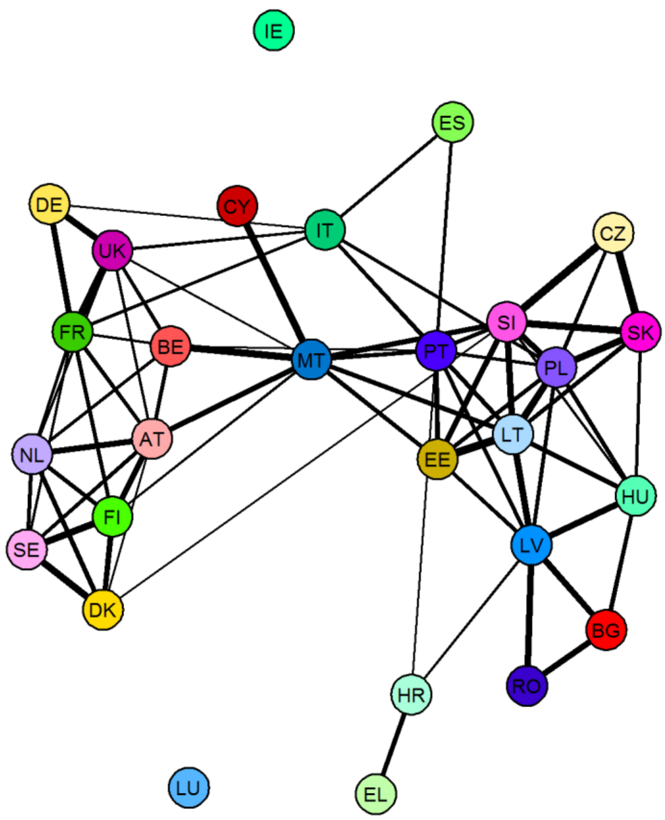
([5]) H_0 = elements of a cluster are equally likely to be over or under the 90th (or 10th) percentile of the distribution of a variable.

([6]) https://github.com/jsollari/EUhackathon2017.

3. Results

Our first approach was to visualize the entire Labour Market Attractiveness set by constructing a social network based on distances between countries (Figure 1). From this analysis we saw a clear separation between Northern and Western European countries and Eastern European countries, while Southern European countries seemed to somewhat make the bridge between these two main blocks. More in detail, we observed a group formed by Denmark (DK), Finland (FI), Sweden (SE), Netherlands (NL) and Austria (AT), and another by France (FR), Germany (DE) and the United Kingdom (UK). On the other hand, Czech Republic (CZ), Estonia (EE), Lithuania (LT), Poland (PL), Slovenia (SI) and Slovakia (SK) seemed to form a group, while Bulgaria (BG), Hungary (HU), Latvia (LV) and Romania (RO) seemed to form another one. Belgium (BE), Malta (MT) and Portugal (PT) were positioned in the centre of the network. We also observed strong links between pairs of countries, i.e. Greece (EL) and Croatia (HR), Italy (IT) and Spain (ES), and Cyprus (CY) and Malta. Finally, both Luxemburg (LU) and Ireland (IE) seemed to be far apart from all the other countries.

Figure 1: Country social network using Labour Market Attractiveness set



Following the construction of a country network, we performed a clustering analysis on the data (Figure 2). This analysis gave a more detailed overview of the grouping with very consistent clusters (separation values always above 2, Table 3). The Northern and Western European countries were further divided in Cluster 4 (DE, UK, FR) and Cluster 5 (DK, SE, FI, NL), while the Eastern European countries were divided in Cluster 2 (BG, RO, LV, HU) and Cluster 3 (CZ, SK, SI). As in the previous analysis, some countries were paired, such as in Cluster 7 (EL, HR) and in Cluster 8 (ES, IT), while LU and IE remained separated in Clusters 9 and 10, respectively. Interestingly, we observed two considerably heterogeneous groupings Cluster 1 (MT, CY, BE, AT) and Cluster 6 (EE, LT, PT, PL). Overall, the SNA and the PAM analysis gave very consistent results.

Figure 2: **Cluster analysis using Labour Market Attractiveness set. Average silhouette width for all possible number of clusters (left). Silhouette width of regions considered for 10 clusters (right)**

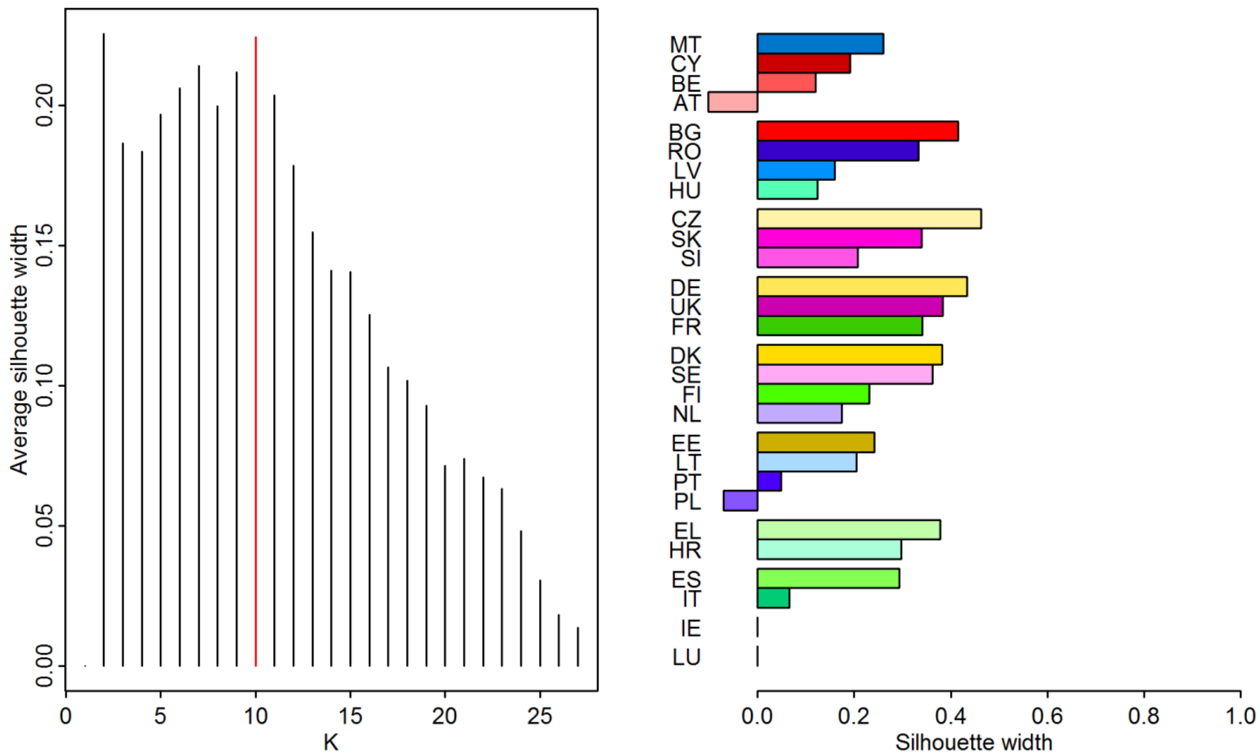


Table 3: **Description of clusters**

cluster	NUTS([a])	n	sep
AT-BE-CY-MT	MT, CY, BE, AT	4	2.66
BG-HU-LV-RO	BG, RO, LV, HU	4	2.49
CZ-SK-SI	CZ, SK, SI	3	2.31
DE-FR-UK	DE, UK, FR	3	3.19
DK-FI-NL-SE	DK, SE, FI, NL	4	2.66
EE-LT-PL-PT	EE, LT, PT, PL	4	2.31
EL-HR	EL, HR	2	3.53
ES-IT	ES, IT	2	3.10
IE	IE	1	3.75
LU	LU	1	4.68

([a]) Order of countries reflects belongingness to cluster (i.e. silhouette width).

n, number of elements of the cluster; sep, separation of the cluster (i.e. minimal dissimilarity between an observation of the cluster and an observation of another cluster).

In order to obtain a general characterization of the clusters, we looked at variables that provided a higher separation between the groupings, namely: Gross Domestic Product (GDP), public expenditure in higher education, total population size, disposable income and proportion of adults working in Financial and insurance activities (see Annex 5). For a characterization of each specific cluster, we further performed an ORA on discretized variables (Table 4). Thus, we found that Cluster 1 (AT, BE, CY, MT) was characterized as having small-sized populations, high proportions of youngsters and high proportions of employed youngsters with higher education. Cluster 2 (BG, HU, LV, RO) was mostly characterized as having high rates of poverty, low disposable incomes and low expenditures in higher-education. Cluster 3 (CZ, SK, SI) was characterized as having high proportions of adults in the population, of which the employed ones had high proportions achieving secondary education and low proportions achieving only primary education. Cluster 4 (DE, FR, UK) was characterized as having large-sized populations with high proportions of children and high disposable incomes. Cluster 5 (DK, FI, NL, SE) was characterized as having high rates of employed youngsters and adults, high expenditures in higher education and low rates of poverty. Cluster 6 (EE, LT, PL, PT) was characterized as having high proportions of employed elders. Cluster 7 (EL, HR) was characterized as having high unemployment rates of youngsters and low employment rates of adults. Finally, Cluster 8 (ES, IT) was characterized as having both low proportions of youngsters in the population and of employed youngsters. Regarding the single-element Clusters 9 and 10, we were unable to perform ORA since obtaining significant statistics in these cases is considerably difficult. Nonetheless, we note that IE (Cluster 9) had the highest proportion of children and the highest Gross Value Added growth (GVAgr) of the whole EU-28 countries, while LU (Cluster 10) had the highest proportion of employed adults with higher education and the highest GDP.

Table 4: Characterization of clusters

cluster	Over-represented variables
AT-BE-CY-MT	> P90: emp_Y[15–24]_ED[5–8]; emp_Y[15–24]_Nace[F]; pop_Y[15–24]; rooms_pp. < P10: pop_Total.
BG-HU-LV-RO	> P90: AROPE; emp_Y[15–24]_Nace[J]; mat_depriv. < P10: disp_income; earn_OC[1–9]_Nace[B–F]; earn_OC[2–5, 7–9]_Nace[G-N]; earn_OC[1–9]_Nace[P–S]; emp_Y[15–24, 25–64]_Nace[O–Q]; expend_ED[5–8]; GDP; training.
CZ-SK-SI	> P90: emp_Y[15–24, 25–64]_ED[3–4]; emp_Y[15–24]_Nace[B–E]; emp_Y[25–64]_Nace[B-E, F]; pop_Y[25–64]. < P10: emp_Y[25–64]_ED[0–2].
DE-FR-UK	> P90: disp_income; pop_Total; pop_Y[0–14]. < P10: emp_Y[15–24]_Nace[A].
DK-FI-NL-SE	> P90: earn_OC[7–9]_Nace[B–F]; earn_OC[5, 9]_Nace[G–N]; earn_OC[6, 8]_Nace[P–S]; emp_Y[15–24, 25–64]; emp_Y[15–24]_ED[0–2]; emp_Y[15–24]_Nace[M–N]; emp_Y[25–64]_Nace[J, M–N, O–Q]; expend_ED[5–8]; pop_Y[65–74]; training. < P10: ARPR; AROPE; emp_Y[15–24]_ED[3–4, 5–8]; emp_Y[25–64]_Nace[G–I]; mat_depriv; pop_Y[25–64].
EE-LT-PL-PT	> P90: emp_Y[GE65]. < P10: earn_OC[1]_Nace[G–N]; emp_Y[25–64]_Nace[J, K].
EL-HR	> P90: unemp_Y[15–24]. < P10: emp_Y[25–64]; emp_Y[25–64]_Nace[L].
ES-IT	> P90: none. < P10: emp_Y[15–24]; pop_Y[15–24].
IE	> P90: none. < P10: none.
LU	> P90: none. < P10: none.

For the inferential part of the framework, we first calculated simple Spearman correlations between each variable of the Labour Market Attractiveness set and the labour market indicators (Annex 6). We noted that while Skills mismatch was only significantly associated (p-value < 0.05) to 'emp_Y[15–24]' (Proportion of employed youth), Mobility was associated to more than 40 variables and Emigration to about 10 variables. Therefore, our next approach was to perform a model selection using multivariate linear regression models to find which group of variables from the Labour Market Attractiveness set could explain better the labour market indicators. We observed that Skills Mismatch across EU-28 could be well explained using ‘emp_Y[15–24]’ and ‘emp_Y[15–24]_Nace[M–N]’ (Proportion of employed youth in Professional, scientific and technical activities; administrative and support service activities) with a $R^2 = 0.94$ (Table 5). Mobility was best modelled considering ‘emp_Y[25–64]_Nace[L]’ (Proportion of employed adults in Real estate activities), ‘emp_Y[25–64]_Nace[K]’ (Proportion of employed adults in Financial and insurance activities) and ‘emp_Y[15–24]_Nace[B–E]’ (Proportion of employed youths in Industry) achieving a $R^2 = 0.79$ (Table 6). Regarding Emigration the variables of the best model were ‘emp_Y[25–64]_Nace[K]’ (Proportion of employed adults in Financial and insurance activities), ‘emp_Y[15–24]_ED[5–8]’ (Proportion of employed youths with Tertiary Education), ‘emp_Y[15–24]_Nace[O–Q]’ (Proportion of employed youths in Public administration, defence, education, human health and social work activities), ‘pop_Total’ (Total population size) and ‘emp_Y[15–24]_Nace[B–E]’ (Proportion of employed youth in Industry) with a $R^2 = 0.83$ (Table 7).

Table 5: Summary Table for best multivariate model for Skills Mismatch

Variables	Estimate	Std. Error	t-value	Pr(>|t-value|)
(Intercept)	100.60	8.694	11.570	<0.001
emp_Y15–24	-3.18	0.356	-8.920	<0.001
emp_Y15–24_NaceM-N	6.56	1.000	6.560	0.001

skills_mismatch ~ emp_Y15–24 + emp_Y15–25_NaceM–N

RSS = 5.51 (5 d.f.)
$R^2 = 0.94$, R^2-adjusted = 0.92
F(2,5) = 43.76 (p-value < 0.001)

Note: 20 data entries and 34 variables were removed to keep only complete-cases; 10 variables highly correlated among them ($\rho > 0.90$) and 2 variables least correlated with dependent variable ($\rho < 0.06$) were removed to run analysis at the most with 30 variables.

Table 6: Summary Table for best multivariate model for Mobility

Variables	Estimate	Std. Error	t-value	Pr(>|t-value|)
(Intercept)	1.82	6.196	0.290	0.772
emp_Y25–64_NaceK	4.61	0.711	6.470	<0.001
emp_Y25–64_NaceL	10.04	2.892	3.470	0.002
emp_Y15–24_NaceB–E	-0.38	0.198	-1.930	0.067

mobility ~ emp_Y25–64_NaceK + emp_Y25–64_NaceL + emp_Y15–24_NaceB–E

RSS = 7.10 (21 d.f.)
$R^2 = 0.79$, R^2-adjusted = 0.76
F(3,21) = 25.85 (p-value < 0.001)

Note: 3 data entries and 34 variables were removed to keep only complete-cases; 1 variables highly correlated among them ($\rho > 0.90$) and 11 variables least correlated with dependent variable ($\rho < 0.15$) were removed to run analysis at the most with 30 variables.

Table 7: Summary Table for best multivariate model for Emigration

Variables	Estimate	Std. Error	t-value	Pr(>|t-value|)
(Intercept)	0.52	0.276	1.900	0.071
emp_Y25–64_NaceK	0.18	0.031	5.790	<0.001
emp_Y15–24_ED5–8	0.03	0.006	4.420	<0.001
emp_Y15–24_NaceO–Q	-0.03	0.011	-2.880	0.009
pop_Total	0.00	0.000	-2.500	0.020
emp_Y15–24_NaceB–E	-0.01	0.008	-1.870	0.075

emigration ~ emp_Y25–64_NaceK + emp_Y15–24_ED5–8 + emp_Y15–24_NaceO–Q + pop_Total + emp_Y15–24_NaceB–E RSS = 0.27 (22 d.f.) R^2 = 0.83, R^2-adjusted = 0.79 F(5,22) = 21.55 (p-value < 0.001)

Note: 34 variables were removed to keep only complete-cases; 1 variable highly correlated among them (ρ > 0.90) and 11 variables least correlated with dependent variable (ρ < 0. 11) were removed to run analysis at the most with 30 variables.

Our final approach for the inferential part was to use WCNA to study associations using a reduced variable set. Indeed, we were able to reduce the Labour Market Attractiveness set to 6 Eigenvariables, namely, 'Unemployment', 'Poverty', 'Ageing Population', 'Education (Employed Adults)', 'Employment' and 'Earnings structure' (Table 8). Considering these Eigenvariables (Table 9), we found that Skills Mismatch is very negatively associated to 'Employment' (ρ = -0.69, p-value = 0.058) and moderately negatively associated to 'Education (Employed Adults)' (ρ = -0.38, p-value = 0.352), while being moderately associated to 'Poverty' (ρ = 0.38, p-value = 0.352) and 'Unemployment' (ρ = 0.36, p-value = 0.385). Mobility is strongly associated to 'Earnings structure' (ρ = 0.59, p-value = 0.002) and moderately associated to 'Employment' (ρ = 0.35, p-value = 0.082). Lastly, Emigration is very negatively associated to 'Education (Employed Adults)' (ρ = -0.50, p-value = 0.007) and moderately negatively associated to Ageing Population (ρ = -0.36, p-value = 0.063).

Table 8: Eigenvariables of Labour Market Attractiveness set

Eigenvariables	n	mean MM	Variables (>0.75 MM)
Unemployment	3	0.83	+: emp_Y[15–24]_Nace[G–I]; unemp_Y[15–24, GE25]. -: none.
Poverty	2	0.95	+: ARPR; AROPE. -: none.
Ageing Population	2	0.86	+: pop_Y[GE75]. -: pop_Y[15–24].
Education (Employed Adults)	4	0.71	+: emp_Y[25–64]_ED[3–4]. -: emp_Y[25–64]_ED[0–2]
Employment	4	0.80	+: emp_Y[15–24, 25–64] -: none.
Earnings	51	0.76	+: earn_OC[1–5, 7–9]_Nace[B–F]; earn_OC[1–5, 7–9]_Nace[G–N]; earn_OC[1–5, 9]_Nace[P–S]; emp_T[P]; emp_Y[25–64]_Nace[M_N, O–Q]; GDP; rooms_pp; training; -: mat_depriv.

n, number of variables grouped in Eigenvariable; MM, module membership calculated as the correlation to belonging Eigenvariable.

Note: 8 variables with more than 15% of missing data were removed. 2 variables did not group into any Eigenvariable.

Table 9: Correlation between labour market indicators and Eigenvariables

Eigenvariables	Skills Mismatch	Mobility	Emigration
Unemployed	0.36 (0.385)	-	-
Poverty	0.38 (0.352)	-	-
Ageing Population	-	-	-0.36 (0.063)
Education (Employed Adults)	-0.38 (0.352)	-	-0.50 (0.007)
Employed	-0.69 (0.058)	0.35 (0.082)	-
Earnings	-	0.59 (0.002)	-

(-) correlations between -0.30 and 0.30.

Note: Correlations calculated using Spearman correlation (p-values between brackets).

4. Discussion and conclusions

The use of the Labour Market Attractiveness set aimed to capture the heterogeneity of the EU global labour market. For this purpose, we chose a broad collection of socio-demographic and economic information. The chosen set of variables seemed to successfully describe the EU space as the country network built showed complex interactions between the regions. Indeed, there seems to be a main separation between Northern and Western Europe and Eastern Europe, which at a finer detail revealed a far more complex net of connections. Thus, we observed a strongly connected group of Scandinavian countries (DK, FI and SE), a group of the most populous countries (FR, DE and UK), two distinct groups of Eastern European countries (CZ, EE, LT, PL, SI and SK; and BG, HU, LV and RO), several pairings (EL and HR; IT and ES; and CY and MT), and two single-element groups (LU; and IE).

The social network approach was complemented using a clustering analysis coupled with ORA to extract the clusters defining characteristics. These characteristics can reflect different degrees of attractiveness depending on the stakeholder. Thus, Cluster 3 (CZ, SI and SK) can be more attractive when looking for labour forces composed mostly by adults, while Cluster 1 (AT, BE, CY and MT) can be attractive when looking for younger labour forces. Similarly, Cluster 2 (BG, LV, HU and RO) can be attractive for enterprises looking for low-waged economies, while Cluster 5 (DK, SE, FI and NL) and Cluster 4 (FR, DE and UK) can be attractive for job seekers looking for high-paid jobs. Stakeholders interested in labour markets fairly open to elders can look at Cluster 6 (EE, LT, PL and PT). Nevertheless, characteristics such as high poverty rates, high unemployment, low-level of education and low public expenditure in education are generally unattractive.

The main goal for developing this exploration framework was to extract useful information from data to help policy-makers define strategies to tackle labour market problems. In fact, we argue that the characteristics extracted from the data can be invaluable to define strategies more suitable for each particular regional case. For example, taking into account countries characteristics such as ageing labour forces (Cluster 6: EE, LT, PL and PT), ageing population (Cluster 5: DK, FI, NL and SE; and Cluster 8: ES and IT) or highly skilled labour forces (Cluster 1: AT, BE, CY and MT; and Cluster 10: LU) can be of utmost importance when implementing policies to reduce Skills mismatch. Moreover, knowing of high unemployment (Cluster 7: EL and HR) and low access to employment (Cluster 8: ES and IT) can be important to diagnose potential labour market problems.

Using the inferential part of the framework, we aimed to establish associations between indicators relevant to labour market (i.e. Skills mismatch, Mobility, Emigration) and the characteristics of the labour market itself. Interestingly, we noticed that the clustering scheme did not reflect the distribution of values of the indicators, thus, we considered the countries separately. Using multivariate linear regressions, we found that all the indicators could be successfully modelled using variables from the Labour Market Attractiveness set with R^2 between 0.79 and 0.94. As mentioned before, results from a model-selection analysis need to be looked at carefully, particularly, because the best models often overshadow other interesting ones. Nevertheless, we noted that, albeit being defined only by 8 points, Skills mismatch could be well captured by considering information on employed youth. In particular, there seems to be an inverse relation between employed youth and Skills mismatch. Regarding Mobility, we found that its variation can be explained well by employed adults in Real estate activities and in Financial and insurance, as well as employed youths in Industry. But, while the formers are positively associated, the latter is negatively associated to Mobility. Consistently, Emigration seems also to be positively related to employed adults in Financial and insurance activities and negatively related to employed youths in Industry. Population size seems to play a role in Emigration too, i.e. the bigger the population of a country, the lower its emigration rate. On the other hand, we observed that the more employed youths with higher education, the higher a country's emigration rate.

The results from the model selection analysis were corroborated by the ones from WCNA. In fact, we found the same negative association between Skills mismatch and employment, but we observed also a negative association with education of employed adults. Furthermore, Skills mismatch seems to be also positively associated to poverty and unemployment. Mobility was found again to be associated to employment. Moreover, there seems to be an unsurprising association between mobility towards a country and its earning structure. Lastly, using WCNA, we found a negative association between education of employed adults and emigration, but we also found that, as expected, as the population ages, it becomes less willing to emigrate.

Note, however, that results from association studies, such as the one presented here, need to be considered carefully. Particularly when claiming cause-effect relationships. One limitation of this type of studies is exactly that characteristics of a country can go hand-in-hand with socio-economic or demographic indicators without a causal effect. These associations are often because of historical or contextual reasons, or due to a third-factor.

We presented a framework that defines important indicators of labour market (i.e. Skills mismatch, Mobility, Emigration), and test their association to characteristic of EU labour market extracted using a developed Labour Market Attractiveness set. This framework can be important in helping to better understand the dynamics between socio-economic and demographic characteristics and relevant aspects of the labour market. Moreover, these studies can not only provide better understandings, but also provide possible strategies to tackle labour market related problems, such as mismatch between local supply and demand of labour force and/or of specific labour skills. As such, they can provide invaluable tools for helping policy-makers to define strategies to shape labour force to the needs of a fast-changing global labour market.

List of acronyms

AICc – corrected Akaike Information Criteria

AROPE – At-risk-of-poverty and social exclusion

ARPR – At-risk-of-poverty rate

ESCO – European Skills, Qualifications and Occupations

EU – European Union

GDP – Gross Domestic Product

GVAgr – Gross Value Added growth

ISCED – International Standard Classification of Education

ISCED-F – International Standard Classification of Fields of Education and Training

ISCO – International Standard Classification of Occupations

NACE – Statistical classification of economic activities in the European Community

ORA – Over-representation analysis

PAM – Partition-around-medoids

SNA – Social network analysis

WCNA – Weighted correlation network analysis

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ANNEX 1

Eurostat datasets for Labour Market Attractiveness set

dataset	description	year	units
demo_r_d2jan	Population	2014	NR
earn_ses_hourly	Structure of earnings: hourly earnings	2014	MN_PPS
educ_uoe_fine06	Total public expenditure on education	2013	PC_GDP
ilc_li41	At-risk-of-poverty rate	2014	PC_POP
ilc_lvhl21	People living in households with very low work intensity	2014	PC_POP_YLE60
ilc_lvho04n	Average number of rooms	2014	AVG
ilc_mddd21	Severe material deprivation rate	2014	PC_POP
ilc_peps11	People at risk of poverty or social exclusion	2014	PC_POP
lfst_r_lfe2eedu	Employment by educational attainment level (ISCED 11)	2014	THS
lfst_r_lfe2eftpt	Employment by full-time/part-time	2014	THS
lfst_r_lfe2emp	Employment	2014	THS
lfst_r_lfe2en2	Employment by economic activity (NACE Rev. 2)	2014	THS
lfst_r_lfu3pers	Unemployment	2014	THS
nama_10r_2gdp	Gross domestic product	2014	PPS_HAB
nama_10r_2gvagr	Real growth rate of regional gross value added	2014	PCH_PRE
nama_10r_2hhinc	Income of households	2013	PPCS_HAB
trng_lfse_04	Participation rate in education and training	2014	PC_POP_Y25–64

NR, Number; MN_PPS, Mean by group in Purchasing Power Standard; PC_GDP, Percentage of Gross.

ANNEX 2

Eurostat datasets for labour market indicators

dataset	description	year	units
educ_uoe_grad02	Graduates by education level, programme orientation, sex and field of education	2014	NR
jvs_a_nace2	Job vacancy statistics by occupation, NUTS 2 regions and NACE Rev. 2 activity - annual data (2008–15)	2014	NR
lfso_14leeow	Employees by migration status, educational attainment level, occupation and working time	2014	THS
migr_emi2	Emigration by age and sex	2014	NR

NR, Number; THS, Thousand.

ANNEX 3

Summary statistics on Labour Market Attractiveness set

variable	mean	n	stdev	cv
ARPR	16.84	28	3.822	0.227
AROPE	24.88	28	7.003	0.281
earn_OC[1]_Nace[B–F]	21.99	26	8.169	0.371
earn_OC[1]_Nace[G–N]	21.66	26	7.039	0.325
earn_OC[1]_Nace[P–S]	19.65	26	8.084	0.411
earn_OC[2]_Nace[B–F]	16.68	26	6.406	0.384
earn_OC[2]_Nace[G–N]	16.88	26	5.418	0.321
earn_OC[2]_Nace[P–S]	16.12	26	7.205	0.447
earn_OC[3]_Nace[B–F]	12.73	26	5.018	0.394
earn_OC[3]_Nace[G–N]	13.05	26	4.510	0.346
earn_OC[3]_Nace[P–S]	11.83	26	5.337	0.451
earn_OC[4]_Nace[B–F]	10.54	26	4.248	0.403
earn_OC[4]_Nace[G–N]	10.50	26	3.987	0.380
earn_OC[4]_Nace[P–S]	10.31	26	4.770	0.463
earn_OC[5]_Nace[B–F]	8.36	25	3.722	0.445
earn_OC[5]_Nace[G–N]	8.23	26	3.357	0.408
earn_OC[5]_Nace[P–S]	8.78	26	4.308	0.491
earn_OC[6]_Nace[B–F]	7.34	13	4.668	0.636
earn_OC[6]_Nace[G–N]	8.37	17	3.961	0.473
earn_OC[6]_Nace[P–S]	8.08	16	4.048	0.501
earn_OC[7]_Nace[B–F]	8.84	26	3.997	0.452
earn_OC[7]_Nace[G–N]	8.45	26	3.605	0.427
earn_OC[7]_Nace[P–S]	8.45	23	4.280	0.506
earn_OC[8]_Nace[B–F]	9.07	26	4.024	0.444
earn_OC[8]_Nace[G–N]	8.95	26	3.649	0.408
earn_OC[8]_Nace[P–S]	7.49	23	3.492	0.466
earn_OC[9]_Nace[B–F]	8.01	26	3.601	0.449
earn_OC[9]_Nace[G–N]	7.30	26	3.239	0.444
earn_OC[9]_Nace[P–S]	7.56	26	3.741	0.495
emp_T[F]	47.40	28	5.471	0.115
emp_T[P]	9.55	28	6.764	0.708
emp_Y[15–24]	29.93	28	12.472	0.417
emp_Y[25–64]	70.82	28	5.965	0.084
emp_Y[GE65]	5.72	28	3.010	0.527
emp_Y[15–24]_ED[0–2]	21.51	28	12.135	0.564
emp_Y[15–24]_ED[3–4]	62.21	28	13.026	0.209
emp_Y[15–24]_ED[5–8]	16.02	28	8.998	0.562
emp_Y[25–64]_ED[0–2]	16.40	28	11.835	0.722
emp_Y[25–64]_ED[3–4]	47.84	28	13.232	0.277
emp_Y[25–64]_ED[5–8]	35.41	28	8.727	0.246
emp_Y[15–24]_Nace[A]	6.38	26	8.063	1.264
emp_Y[15–24]_Nace[B–E]	16.60	28	8.450	0.509
emp_Y[15–24]_Nace[F]	6.81	28	2.239	0.329
emp_Y[15–24]_Nace[G–I]	36.75	28	7.242	0.197
emp_Y[15–24]_Nace[J]	2.63	25	1.030	0.391
emp_Y[15–24]_Nace[K]	1.85	17	0.874	0.473

emp_Y[15–24]_Nace[L]	0.67	8	0.395	0.592
emp_Y[15–24]_Nace[M–N]	7.47	28	2.254	0.302
emp_Y[15–24]_Nace[O–Q]	14.38	28	6.581	0.458
emp_Y[15–24]_Nace[R–U]	6.50	28	2.265	0.348
emp_Y[25–64]_Nace[A]	5.26	28	4.873	0.926
emp_Y[25–64]_Nace[B–E]	17.43	28	5.650	0.324
emp_Y[25–64]_Nace[F]	6.91	28	1.273	0.184
emp_Y[25–64]_Nace[G–I]	23.32	28	3.717	0.159
emp_Y[25–64]_Nace[J]	3.10	28	0.813	0.262
emp_Y[25–64]_Nace[K]	3.29	28	2.225	0.677
emp_Y[25–64]_Nace[L]	0.81	28	0.498	0.616
emp_Y[25–64]_Nace[M–N]	8.74	28	2.145	0.245
emp_Y[25–64]_Nace[O–Q]	25.62	28	5.179	0.202
emp_Y[25–64]_Nace[R–U]	5.06	28	2.067	0.409
expend_ED[5–8]	1.28	23	0.424	0.333
disp_income	13 323	26	3 736	0.280
GDP	26 839	28	11 430	0.426
GVAgr	1.72	25	1.731	1.009
low_work	10.74	28	3.547	0.330
mat_depriv	10.45	28	7.975	0.763
pop_Total	18 106 210	28	23 370 416	1.291
pop_Y[0–14]	15.71	28	1.802	0.115
pop_Y[15–24]	11.68	28	1.097	0.094
pop_Y[25–64]	54.89	28	2.015	0.037
pop_Y[65–74]	9.59	28	1.098	0.114
pop_Y[GE75]	8.14	28	1.403	0.172
rooms_pp	1.60	28	0.367	0.229
training	10.59	28	8.017	0.757
unemp_Y[15–24]	8.75	28	3.508	0.401
unemp_Y[GE25]	6.19	28	3.320	0.536

n, number of countries; stdev, standard deviation; cv, coefficient of variation.

ANNEX 4

Summary statistics on labour market indicators

variable	mean	n	stdev	cv
Skills mismatch	59.3	8	20.035	0.338
Mobility	17.92	25	14.384	0.802
Emigration	0.79	28	0.603	0.764

n, number of countries; stdev, standard deviation; cv, coefficient of variation.

ANNEX 5

Averages of top 10 separator variables of clusters

cluster	GDP (x10^3)	earn_OC[3]_Nace[P–S]	emp_Y[25–64]_Nace[K]	expend_ED[5–8]	earn_OC[7]_Nace[P–S]	earn_OC[5]_Nace[P–S]	earn_OC[9]_Nace[P–S]	pop_Total (x106)	disp_income (x10^3)	earn_OC[4]_Nace[P–S]
AT-BE-CY-MT	28.5	15.3	4.4	1.6	11.6	11.1	9.2	5.2	17.7	12.8
BG-HU-LV-RO	16.0	5.0	2.0	0.8	3.7	3.5	3.1	9.8	8.2	4.5
CZ-SK-SI	22.3	8.2	2.5	1.0	5.6	5.6	4.5	6.0	11.6	7.1
DE-FR-UK	31.2	14.6	3.6	1.5	10.6	10.7	9.3	70.4	18.2	12.5
DK-FI-NL-SE	33.5	15.6	2.9	2.0	13.5	13.5	11.5	9.4	15.7	14.3
EE-LT-PL-PT	20.4	6.7	1.9	1.2	4.9	4.5	4.0	13.2	11.1	5.8
EL-HR	18.0	-	2.6	-	-	-	-	7.6	10.3	-
ES-IT	25.7	12.6	2.8	0.9	9.0	9.5	8.7	5.4	15.1	11.0
IE	36.8	20.2	5.0	1.3	16.3	15.2	14.1	4.6	13.8	18.2
LU	73.0	23.4	13.2	-	-	14.8	12.8	0.6	-	19.5
sep = Var_b/Var_w	34.395	30.24	28.781	20.025	19.772	19.02	17.749	17.176	17.024	14.995

(-) not available.

Var_b, Variation between clusters; Var_w, Variation within clusters.

ANNEX 6

Correlation between labour market indicators and Labour Market Attractiveness

variable	Skills mismatch		Mobility		Emigration	
	statistic	p-value	statistic	p-value	statistic	p-value
ARPR	0.33	0.420	-0.09	0.659	0.19	0.322
AROPE	0.38	0.352	-0.25	0.237	0.24	0.223
earn_OC[1]_Nace[B–F]	0.00	1.000	0.34	0.115	-0.07	0.749
earn_OC[1]_Nace[G–N]	0.21	0.610	0.39	0.068	0.02	0.917
earn_OC[1]_Nace[P–S]	0.02	0.955	0.43	0.042	0.14	0.489
earn_OC[2]_Nace[B–F]	-0.10	0.821	0.43	0.040	0.08	0.707
earn_OC[2]_Nace[G–N]	-0.14	0.736	0.48	0.022	0.10	0.639
earn_OC[2]_Nace[P–S]	-0.07	0.867	0.47	0.023	0.22	0.281
earn_OC[3]_Nace[B–F]	-0.12	0.779	0.49	0.017	0.14	0.483
earn_OC[3]_Nace[G–N]	-0.02	0.955	0.48	0.020	0.10	0.612
earn_OC[3]_Nace[P–S]	-0.10	0.823	0.55	0.006	0.24	0.241
earn_OC[4]_Nace[B–F]	-0.24	0.570	0.47	0.025	0.10	0.625
earn_OC[4]_Nace[G–N]	-0.07	0.867	0.51	0.013	0.16	0.444
earn_OC[4]_Nace[P–S]	-0.12	0.779	0.47	0.023	0.24	0.245
earn_OC[5]_Nace[B–F]	-0.07	0.867	0.50	0.018	0.08	0.688
earn_OC[5]_Nace[G–N]	-0.05	0.910	0.43	0.039	0.10	0.610
earn_OC[5]_Nace[P–S]	-0.24	0.570	0.47	0.025	0.18	0.371
earn_OC[6]_Nace[B–F]	-0.31	0.456	0.37	0.259	-0.09	0.775
earn_OC[6]_Nace[G–N]	-0.21	0.645	0.61	0.016	0.01	0.978
earn_OC[6]_Nace[P–S]	-0.03	0.957	0.28	0.334	-0.04	0.888
earn_OC[7]_Nace[B–F]	-0.40	0.320	0.48	0.022	0.08	0.709
earn_OC[7]_Nace[G–N]	-0.31	0.456	0.45	0.031	0.15	0.454
earn_OC[7]_Nace[P–S]	-0.19	0.651	0.43	0.057	0.14	0.529
earn_OC[8]_Nace[B–F]	-0.33	0.420	0.43	0.039	0.09	0.677
earn_OC[8]_Nace[G–N]	-0.36	0.385	0.55	0.006	0.25	0.225
earn_OC[8]_Nace[P–S]	-0.31	0.456	0.53	0.015	0.18	0.422
earn_OC[9]_Nace[B–F]	-0.24	0.570	0.49	0.019	0.08	0.699
earn_OC[9]_Nace[G–N]	-0.05	0.911	0.47	0.025	0.13	0.537
earn_OC[9]_Nace[P–S]	-0.07	0.867	0.46	0.029	0.17	0.399
emp_T[F]	-0.57	0.139	-0.23	0.265	-0.28	0.149
emp_T[P]	-0.17	0.693	0.57	0.003	0.19	0.343
emp_Y[15–24]	-0.76	0.028	0.24	0.254	0.01	0.976
emp_Y[25–64]	-0.64	0.086	0.42	0.034	-0.18	0.352
emp_Y[GE65]	0.02	0.955	0.21	0.314	0.16	0.418
emp_Y[15–24]_ED[0–2]	0.24	0.570	0.22	0.291	0.14	0.491
emp_Y[15–24]_ED[3–4]	-0.19	0.651	-0.45	0.025	-0.53	0.004
emp_Y[15–24]_ED[5–8]	0.29	0.493	0.37	0.066	0.56	0.002
emp_Y[25–64]_ED[0–2]	0.52	0.183	0.11	0.593	0.34	0.080
emp_Y[25–64]_ED[3–4]	-0.29	0.493	-0.38	0.060	-0.52	0.005
emp_Y[25–64]_ED[5–8]	-0.33	0.420	0.57	0.003	0.47	0.012
emp_Y[15–24]_Nace[A]	0.36	0.385	-0.34	0.109	0.39	0.051
emp_Y[15–24]_Nace[B–E]	0.31	0.456	-0.58	0.002	-0.56	0.002
emp_Y[15–24]_Nace[F]	-0.55	0.160	0.19	0.359	-0.31	0.109
emp_Y[15–24]_Nace[G–I]	0.29	0.493	0.06	0.784	0.22	0.269

emp_Y[15–24]_Nace[J]	0.14	0.736	0.17	0.462	0.16	0.434
emp_Y[15–24]_Nace[K]	0.40	0.600	0.25	0.383	0.16	0.535
emp_Y[15–24]_Nace[L]	-	-	0.64	0.119	-0.17	0.693
emp_Y[15–24]_NaceM_N	0.21	0.610	0.39	0.053	0.08	0.684
emp_Y[15–24]_Nace[O–Q]	-0.52	0.183	0.55	0.005	0.04	0.851
emp_Y[15–24]_Nace[R–U]	-0.45	0.260	0.53	0.006	0.27	0.171
emp_Y[25–64]_Nace[A]	0.24	0.570	-0.43	0.032	0.13	0.495
emp_Y[25–64]_Nace[B–E]	0.24	0.570	-0.59	0.002	-0.58	0.001
emp_Y[25–64]_Nace[F]	-0.50	0.207	-0.11	0.588	-0.34	0.072
emp_Y[25–64]_Nace[G–I]	0.33	0.420	-0.10	0.621	0.18	0.358
emp_Y[25–64]_Nace[J]	-0.69	0.058	0.58	0.002	0.07	0.711
emp_Y[25–64]_Nace[K]	0.00	1.000	0.47	0.017	0.38	0.044
emp_Y[25–64]_Nace[L]	-0.52	0.183	0.30	0.152	-0.15	0.433
emp_Y[25–64]_NaceM_N	-0.19	0.651	0.51	0.008	0.07	0.707
emp_Y[25–64]_Nace[O–Q]	-0.21	0.610	0.41	0.040	0.15	0.455
emp_Y[25–64]_Nace[R–U]	-0.14	0.736	0.51	0.009	0.23	0.239
expend_ED[5–8]	-0.07	0.867	0.40	0.071	0.13	0.561
disp_income	-0.07	0.867	0.46	0.028	-0.03	0.885
GDP	-0.31	0.456	0.51	0.009	0.10	0.603
GVAgr	-0.04	0.939	-0.15	0.496	0.20	0.350
low_work	0.29	0.493	-0.09	0.667	0.06	0.769
mat_depriv	0.45	0.260	-0.49	0.014	0.11	0.565
pop_Total	0.52	0.183	-0.24	0.253	-0.36	0.063
pop_Y[0–14]	-0.45	0.260	0.35	0.090	0.23	0.244
pop_Y[15–24]	-0.36	0.385	0.13	0.531	0.32	0.097
pop_Y[25–64]	0.10	0.823	-0.31	0.129	-0.03	0.879
pop_Y[65–74]	-0.19	0.651	-0.10	0.637	-0.43	0.023
pop_Y[GE75]	0.10	0.823	0.14	0.519	-0.22	0.251
rooms_pp	-0.27	0.520	0.55	0.004	0.38	0.046
training	-0.35	0.399	0.57	0.003	-0.11	0.576
unemp_Y[15–24]	0.02	0.955	0.00	0.983	0.07	0.711
unemp_Y[GE25]	0.29	0.493	-0.09	0.682	0.07	0.719

(-) Only two datapoints available.

ANNEX 7

Information on ISCED 11 education levels, ISCED-F 13 fields of education, ISCO-O8 job titles, EU-28 countries and NACE Rev. 2 economic activity sectors

ISCED 11	
0–2	Less than primary, primary and lower secondary education
3–4	Upper secondary and post-secondary non-tertiary education
5–8	Tertiary education
ISCED-F 13	
00	Generic programmes and qualifications
01	Education
02	Arts and humanities
03	Social sciences, journalism and information
04	Business, administration and law
05	Natural sciences, mathematics and statistics
06	Information and Communication Technologies (ICTs)
07	Engineering, manufacturing and construction
08	Agriculture, forestry, fisheries and veterinary
09	Health and welfare
10	Services
99	Unknown
ISCO-08	
0	Armed forces occupations
1	Managers
2	Professionals
3	Technicians and associate professionals
4	Clerical support workers
5	Service and sales workers
6	Skilled agricultural, forestry and fishery workers
7	Craft and related trades workers
8	Plant and machine operators and assemblers
9	Elementary occupations
EU-28	
BE	Belgium
BG	Bulgaria
CZ	Czech Republic
DK	Denmark
DE	Germany (until 1990 former territory of the FRG)
EE	Estonia
IE	Ireland
EL	Greece
ES	Spain
FR	France
HR	Croatia
IT	Italy
CY	Cyprus
LV	Latvia
LT	Lithuania
LU	Luxembourg

HU	Hungary
MT	Malta
NL	Netherlands
AT	Austria
PL	Poland
PT	Portugal
RO	Romania
SI	Slovenia
SK	Slovakia
FI	Finland
SE	Sweden
UK	United Kingdom
NACE Rev. 2	
A	Agriculture, forestry and fishing
B–E	Industry (except construction)
B–F	Industry and construction
F	Construction
G–I	Wholesale and retail trade, transport, accomodation and food service activities
G–N	Services of the business economy
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M–N	Professional, scientific and technical activities; administrative and support service activities
O–Q	Public administration, defence, education, human health and social work activities
P–S	Education; human health and social work activities; arts, entertainment and recreation; other service activities
R–U	Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies

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KS-TC-18-002-EN-N

Labour market attractiveness in the EU

In this work we present a framework developed for the European Big Data Hackathon 2017. This framework is divided in two parts: an exploration part, which is aimed to better understand the EU global labour market and to capture its heterogeneity; and an inferential part, whose goal is to establish associations between characteristics of the EU labour market and indicators designed to capture important aspects of the labour market (i.e. Skills mismatch, Mobility and Emigration).
For the exploration part, we developed the concept of Labour Market Attractiveness, which consists of a combination of socio-economic and demographic variables from Eurostat datasets. Using data mining techniques, such as social networks and clustering analysis, we showed that this combined set consistently captured the country-level heterogeneity in the EU, forming well-defined clusters. For the inferential part, we used model selection analysis and weighted network correlation analyses to establish associations between the characteristics of the EU labour market and the labour market indicators. We argue that the combination of both exploration and inferential parts can disentangle the complex dynamics of the EU labour market and help setting effective policies to tackle typical problems of a fast-changing global labour market environment.

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Publications Office

ISBN 978-92-79-80731-2