Mapping European University cities: Classification of the EU Regions based on their Brain Drain Outcomes

ENDORSE PROJECT

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Abstract

This paper integrates methodologies from two European data sources to present a comprehensive approach for identifying and measuring regional human capital flows across European regions and cities. It estimates indices to measure both the human capital production and the human capital stock of a region. These sub-indices are then summarized into a single statistical index (relative ratio) to determine whether a region experiences brain drain or brain gain, enabling comparable analysis across NUTS-2 European regions. Based on the so-determined brain drain regions, the report examines socio-economic factors influencing brain drain in university regions within the EU-27, utilizing a composite indicator to assess socio-economic performance. The analysis highlights significant regional disparities and identifies various challenges. To address these issues, the research supports the development of tailored study materials for universities, categorized into four types based on regional characteristics. These materials aim to enhance students' entrepreneurial abilities by providing information on required skills, key industries, funding opportunities, and business start-up guidance. By equipping students with targeted knowledge, the project seeks to foster economic development and mitigate brain drain, promoting balanced and equitable growth across the European Union.

Keywords: *Brain drain; human capital production; highly skilled population migration; human capital stock; classification of EU regions and cities; regional development; socio-economic performance index, university-industry-link*

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Introduction

EU regions compete not only with non-EU regions but also among themselves, in order to attract and maintain sufficient flows of talented labour (Mahroum, 2001). This competition for talent has emerged mostly in regions where there are weak incentives for highly-skilled population. The Treaty on European Union and the Treaty on the Functioning of the European Union, in Article 45, states that the free movement of labour, being one of the four economic freedoms of EU citizens (together with the free movement of goods, capital and services) is one of the fundamental principles of the European Union. This freedom of labour movement in combination with the growing international competition for talent has led some regions to a significant loss of highly skilled population to the advantage of other regions that achieve to attract and retain this population.

The phenomenon of brain drain has re-attracted the interest of the scientific community as well as policy makers at national and European level – especially after the financial crisis of 2008. It has been considered as a particularly important issue due its consequences for the economies of the countries of origin of these flows. Given the intensity and consequences of this phenomenon, brain drain is being a central issue in public debate, as well as the subject of political interventions at European, national and regional level. However, the available empirical evidence on the extent of the phenomenon at the regional level remain rather limited, mainly due to the limited availability of reliable and cross-regionally comparable data (Tzeng, 2006).

During the period 2016-2020, according to Eurostat data, the proportion of EU movers in working age with tertiary education has increased dramatically. More specifically, in 2016 30% of all movers were highly educated while in 2020 this proportion increased to 35%. In 2020 just over one third of EU movers had high educational level. In small European countries of destination, such the Netherlands, Ireland, Belgium, Switzerland, and Austria the corresponding percentage was close or more than 50% of total movers. On the other hand, in larger European countries of destination, such as France, Germany, Italy and Spain the proportion of EU movers highly educated was below 40% of all movers (European Commission, 2022).

The sorting of population across space constitutes one of the most critical factors in balanced development. Attracting young and educated people represents the critical factor in shaping living conditions and future challenges for regions and cities. Universities could act as catalysts for the location choices of people across space;

medium and Small size cities could be attractive locations for young students and graduates.

The location choices of young students and University graduates is determined by the balance between *centrifugal* (push) and *centripetal* (pull) factors that are in operation in each locality. Local labor market, quality of the University, cost of living and amenities are considered as 'pull' factors. At the other end, limited employment opportunities, congestion and housing costs are considered among the 'push' factors. All in all, the location decision of young people for education and the location decision after graduation is influenced, *inter alia*, by i) the quality of the University; ii) local attributes such as amenities and the quality of the environment; and iii) labour market and employment opportunities.

There are several reasons that small and medium size cities could be attractive location for students and graduates. First, mobility and migration is higher in younger people. Second, small and medium cities could be the new drivers of growth. Third, cost of living and quality of life is better. Regions and cities, especially the small and medium-sized are trying to attract and retain young students and graduates. However, since this is a zero-sum problem, there are regions and cities that are net brain gainers while there are regions and cities which are net brain drainers.

Utilising data from the European Tertiary Education Register (ETER) for 2016 and complementarily, from Eurostat's database the empirical analysis of the present report aims at:

- Mapping the European University Cities (city level).
- Portraying the Graduates Map at NUTS-3 level.
- Classifying EU regions according to their brain drain outcomes.
- Identifying the brain drain regions at NUTS-2 level.
- Evaluating the overall socio-economic performance of these brain drain regions, going back to NUTS-3 level.
- Categorizing them based on the dimensions of Human Capital, Industry and Government.

This research project aims to develop tailored study materials for universities, grounded in these socio-economic classifications, to enhance the educational experience and entrepreneurial abilities of students. Each university can leverage these classification-specific materials to provide students with detailed knowledge about their region's socio-economic environment.

The rest of this report is structured as follows: Section 1 addresses conceptual issues related to the definition of brain drain, while Section 2 presents a literature review on the determinants of skilled migration flows. Next, in Section 3 the methodology for the estimation of the human capital production and human capital stock indices is presented, as well as the methodology for determining whether a region is brain drain or brain gain. Section 4 describes the two data sources and the sample of the empirical analysis, followed by the empirical findings of the analysis are presented in Section 5. The report concludes by providing in Section 6 a number of policy proposals for regional policies related to the issue of skilled migration.

1. Conceptual Framework

Brain drain as an expression was first used by the British Royal Society during the fifties and sixties, representing the skilled migration to the U.S. and Canada (Ray, 2012). According to Beine, Docquier and Rapoport (2008) "brain drain" is defined as the international mobility of human resources and mainly applies to the migration of relatively highly educated individuals from developing to developed countries. Such mobility of relatively highly educated individuals was seen at the beginning, as detrimental reducing productivity of workers left and causing negative fiscal impacts to sending economies (Docquier and Marfouk, 2006, Groizard, Llull, 2007). Thus, the term emphasised the injustice of the phenomenon (Kone, Ò̀zden, 2017). Most of the studies define "brain drain" as the movement of people with tertiary level of education living in a country other than his/her place of birth (Docquier and Rapoport, 2012). More analytically, it represents university graduates and highly skilled individuals (technical experts, senior managers, doctors, engineers, educators, etc.) that have left their countries to study abroad and do not return to their countries to home preferring to live and work abroad. Talented and educated people leave and settle in richer societies where they can find better life quality and opportunities for themselves and their families (Boc, 2020). Tansel & Gungor define the "brain drain" as the university graduates and highly skilled individuals that after living their countries to study abroad often do not return to their homeland preferring to live and work in the country of their studies (Tansel & Güngör, 2002 in Ray, 2012). Davenport (2004) characterises these brain drains as the most widely recognised of demographic scientific and technical human capital diffusion trends; interpreting the word "brain" as any skill, competency or attribute that is seen as a potential asset and the word "drain" as an exit rate that is greater than the desired level. In addition, Lowell (2003) investigating further the definition issue, states that there are two conditions that necessarily characterize the phenomenon of "brain drain"; first, is the significant loss of highly skilled population and second, is the following adverse economic consequences. More often it refers to any relatively high skilled individual with but not exclusively, tertiary level of education, however according to other approaches; it refers to the migration of "knowledge economy" professions such as engineers, physicians, scientists, IT professionals etc. (Davenport, 2004).

The definition of a regional brain drain used by Cavallini, et al. is the region's loss of individuals with high skills and/or competencies (workers/students) due to permanent emigration (Cavallini, et al., 2018). Jaeger and Kreutzer (2012) distinguish the highly educated migration in four groups: repeat migrants, late migrants, university stayers and non- migrants. Repeat migrants as the students who first, move for their tertiary education to a different region from the region of their secondary education and second, move again, after their tertiary education to a different region to start their professional life. Late migrants are graduates that attend a university in the region of their secondary education and leave after their graduation to start their first job. University stayers are the students who leave the region of their secondary education to study to a university in another region and stay in that region for their first job after graduation and non-migrants are the graduates that studied in a university in their home region and decide to stay and work after their graduation (Jaeger, Kreutzer, 2012). When an individual that experiences in the costs of taking education without gaining the benefits of human capital acquisition, then according to researchers, a different but related phenomenon to brain drain emerges, that of "brain waste" (Mattoo, Neagu and Özden, 2008; Pires, 2015). Reitz describes brain waste as the situation where a skilled individual has a job that either underutilises or not utilises at all, his/her skills, leading to an occupational downgrading (Reitz, 2001).

In the nineties a new literature emerged and showed how brain drain might generate welfare gains for the sending countries and regions, pointing out the "brain gain" effect. Brain drain has also favoured other phenomena such as the "brain regain", the return of the same highly skilled labour and competences that were previously migrated and the phenomenon called by Saxenian "brain circulation", which is the continuous movement and gain-loss of highly skilled labour and competences (Saxenian, 2005; Perrou, Savvaidou, 2019). Todisco, et al. (2013) defined "brain circulation" as the process of globalisation that spreads work, culture, professions and consumption and in which “brain drain” allowing the transfer of knowledge and skills from one place to another pointing out a broader and more appropriate term of brain movement or brain circulation.

2. Determining the Brain Drain Regions in the EU

2.1. Literature Review on the Determinants of Brain Drain

There are factors in three different levels closely interlinked that illustrates a complex interplay between the macro, meso and micro factors behind the individual migration decisions of skilled workers, according to a study of ICF presented in Figure A1 in the Appendix. More specifically, at the macro level factors that act positively are economic environment, labour market conditions, quality of life, working and living conditions, institutional environment and stability and geography, at the *meso* level factors that influence positively, migration policy framework and the size of diaspora communities and at the micro level, the age, gender, level of education, family responsibilities and spoken languages (ICF, 2018).

Undoubtedly, the individual decisions of high skilled people to migrate are complex and influenced by a range of push and pull factors, like all the movements of goods, capital, and services (Table A1 Appendix). However, Todisco et al. (2003) state that a more relevant role is played by pull rather that push factors, when migration concerns highly-skilled population. There are several push factors, defined as the unfavourable structural conditions existing in a region that lead to emigration of human capital, that foster the “brain drain” phenomenon (Bana, 2016). Lutz et al. (2019) state that the phenomenon of “brain drain” is posed and generated by negative factors such as social inequality, differences in earnings and quality of life. Widuto (2019) having studied the phenomenon of “brain drain” in the EU countries too, comes to similar conclusions arguing that bad working and living conditions increase the highly skilled migration. Negative labour market conditions, such as high unemployment rate and low wages among young people work as push factors to the phenomenon of brain drain. Moreover, administrative barriers, economic depression interpreted by the death of enterprises and a bad political environment act as catalysts to the phenomenon (ESPON, 2017). Boc (2020) also argues that high youth unemployment rates and the inability to access to minimal levels of life quality and civic participation generate the “brain drain” phenomenon. Moreover, Perrou and Savvaidou (2019) pointed out the reasons leading to skilled migration (having studied the case of Greece) focusing on the mismatch of supply and demand of skilled labour depending on the profile of the economy, the high rates of unemployment, the underemployment, the political instability, the increased corruption, the general uncertainty, the severe taxation, and the increase of social security contribution. Geographical location has its own influence on the phenomenon because according to Cavallini, et al. (2018) the sending regions are mostly located in the periphery of the EU.

Furthermore, there are also pull factors that foster the phenomenon of "brain drain", defined as favourable structural conditions that lead to immigration of human capital (Bana, 2016). In fact, according to Todisco, et al. (2013) highly skilled migration is influenced by the more attractive, pull factors. Cavallini et al. (2018) argue that there are regions attractive to highly-skilled population because of much better conditions of labour market (e.g. higher employment rates, types of job opportunities available, higher wages, easier access to the labour market, etc.), and much better places to live, especially for young people (e.g. the reputation of a better education system or a better quality of life). In addition, amongst the most important pull factors of the phenomenon, are other economic and social structural conditions, such as active economic growth, robust social security, higher per capita wealth, linguistic similarity, cultural similarity. It has also been noted that any sector-specific strengths, such as a well-established knowledge economy, attract the highly-skilled migration (ESPON, 2017). Moreover, Grecu and Titan (2016) having studied the highly skilled migration in 24 European countries, concluded the strong and positive correlation between "country capacity to retain talent" and life expectancy, quality of overall infrastructure and quality of the educational system.

A project financed within the framework of Interreg IVC called "BrainFlow"[1], concludes that among the most important pull factors of regional "brain drain" as others have already pointed out, are the labour conditions and the quality of life (e.g. affordability and availability of housing, cost of living, quality of the education system, availability of infrastructure, leisure activities, social life and healthcare system). It also states that both, the positive foreign perception of the region and the planning and implementation of city branding strategies highlight the advantages and attracts highly-skilled migration. Support services for business development are also a very

[1] The *"Brain Flow and Knowledge Transfer fostering Innovation in Border Regions"* was financed during the period 2010-2014, within the framework of Interreg IVC.

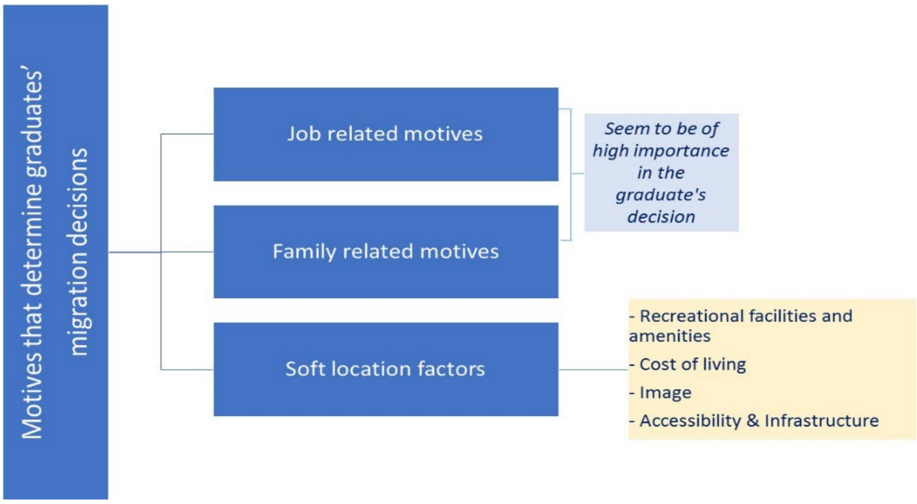
important pull factor according to the "BrainFlow" project. Furthermore, the availability and accessibility of the above information to the talent targeted, particularly for cross border highly skilled migration between neighbouring regions, are also important pull factors. Finally, the "BrainFlow" project highlights as an important pull factor the availability and accessibility of local services that welcome facilitate the relocation of attracted highly-skilled labour (Cavallini, et al., 2018).

Jaeger and Kreutzer (2012) having studied the graduates' migration, present as pull factors of the phenomenon, job offers and high salaries, the existence of entrepreneurial network connections in close distance to universities, that favours the establishment of student's spin-offs and business start-ups and often the different faculties: nationwide research has shown that graduates of Social Sciences Departments remain in their University region, in contrast to graduates of Economics Departments, who more often choose to emigrate. Furthermore, they state that the knowledge of a local economy and labour market (e.g. local job possibilities, duration of job seeking, starting levels of salary and form of job contract[2]) increases the probability of moving to another region or staying in the university region (Figure 1).

One of the main important drivers of intra-EU mobility of young and highly skilled people is the development of the knowledge economy (ESPON, 2018), which is "*able to produce new knowledge from technologically advanced sectors and/or functions present in a territorial area and/or functions present in a territorial area and/or where knowledge is obtained through links (formal or informal) with other economies*" (ESPON 2013). Investigating the criteria to characterise and categorise the knowledge economy, Brinkley and Lee (2007) proposed the presence of knowledge intensive sectors (such as high-tech manufacturing and services; financial and business services; health; education; and creative and cultural services), the establishment of high level scientific institutions, the presence of high educational level of the population and work force in a specific area, and the investments in innovation at firm, individual and sector level.

[2] Jaeger and Kreutzer (2012) argue that a desirable job contract is identified as a permanent employment contract for a full-time-job.

Figure 1: Motives that determine graduate's migration decisions



Source: Jaeger, Kreutzer, 2012

Therefore, a knowledge based regional economy is defined as a regional economy that is linked to positive externalities and specialised either in high-tech sectors, or in scientific functions or capable to obtain knowledge from other economies through cooperation and networking (ESPON, 2018). Boc (2020) argues that the regions where knowledge economy is developed attract highly skilled migrants. These regions have developed physical and technological infrastructure, quality education system, cultural activities, medical care system, good connectivity among businesses and universities.

People setting out to migrate often make educational choices that answer to the destination regions' employment demand rather than local demand, reducing thus the educational benefits for the sending countries and regions (Beine, Docquier, and Rapoport, 2008). Sending countries and regions lose the best part of their workforce; more specifically, the young, healthy, dynamic and most highly educated and qualified population. In fact, it is a net loss for them which have invested in educating their people but they are unable to use these graduates as mature professionals in local economy resources (Todisco, Brandi, Tattolo, 2003). However, "brain drain" has also significant positive and negative impacts. High skilled migration in the sending regions may cause an increase in their human capital level. Wage differences encourage individuals to invest in education and acquire human capital, aiming to migrate and earn higher income abroad that will compensate for their educational expenses. However, only part of the highly educated workforce will migrate and some of them will stay at home, resulting at the end, a higher skilled human capital stock (Stark, Helmenstein and Prskawetz, 1997). For other researchers, “brain drain” relieves unemployment which reaches very high levels in regions and countries where local labour markets are weak and unable to absorb a large number of highly educated individuals (Todisco, Brandi, Tattolo, 2003). Furthermore, researchers state that remittances are a very important positive externality of brain drain, which often finance education in sending countries and regions (Kone, Òzden, 2017). These remittances sent by the highly educated migrants back to their families, also enhances new types of consumption that otherwise would not exist (Todisco, Brandi, Tattolo, 2003). Human capital of sending countries and regions can get to higher levels due to return migration after acquiring human capital abroad (Kone, Òzden, 2017). “Brain drain” may also cause greater diffusion of knowledge, foreign direct investment and trade to the sending countries and regions. It is worth of noting that these highly skilled migrants have more job opportunities to utilize their knowledge and professional skills, that would be otherwise, either underutilized or not utilized at all (Todisco, Brandi, Tattolo, 2003). A positive impact emerges for the receiving countries and regions, receiving and using these human capital resources, acquiring a “brain gain” through this highly skilled migration (Todisco, Brandi, Tattolo, 2003). Therefore, there are positive effects together with the negative effects of brain drain, benefitting both the sending and the receiving countries and regions forming a situation called “brain circulation” (Saxenian, 2005; Todisco, Brandi, Tattolo, 2003).

2.2. Methodology

Available information and data on changes in population stock is a necessary, albeit not a sufficient condition to define brain drain. Information on the skills and educational level of the observed population flows is certainly needed in order to depict to what extent such flows have to do with high skilled population and can be, thereby, characterized as brain drain flows. Nevertheless, there is a limited availability of such information. Eurostat provides information on population by gender, age and region of residence (NUTS-2 & NUTS-3 level), albeit without any further disaggregation by educational level. This limitation means that any information for the magnitude of brain drain at regional cannot be directly obtained from any single dataset among the existing EU official data sources; implying the need for a methodology that could bypass the unavailability of the directly available statistical information for the measurement of brain drain at regional level.

Given that the information on tertiary education outcomes is available only in NUTS-2 level, inevitably, there is a trade-off between how much geographically disaggregated the analysis can be (i.e. NUTS-2, NUTS-3 or even more disaggregate level) and an approach that does incorporate the dimension of the educational level in the definition of brain drain. Dealing with the abovementioned trade-off, the employed approach uses aggregated the level of analysis at NUTS-2 (instead of any other more disaggregated level), which is the most disaggregated geographical unit of analysis that allows for including the dimension of educational level in the identification of the brain drain regions.

To bypass the unavailability of the directly available statistical information for brain drain, the present empirical analysis employs a two-step methodology. In particular, the *first step* focuses on calculating the *Production of Human Capital* in each location, by calculating: i) the number of graduates of ISCED 5 to 8 level in 2016 in each local unit and ii) the number of graduates of ISCED 5 to 8 level per 10,0000 persons aged 20-34 in 2016 in each local unit (in order to make this information comparable across regions with different population size, allowing thus for ranking the EU regions based on their performance in production of Human Capital. Then, using the information on the absolute number of graduates of ISCED 5 to 8 level in 2016 in each local unit, allows for calculating a *Production of Human Capital index* based on each region's share to the total number graduates of ISCED 5 to 8 level in all the selected EU regions of the sample (i.e. the sum of graduates all the selected regions) defined as follows:

$$\textbf{\textit{Production of Human Capital index of } } \boldsymbol{X_i} \textbf{\textit{ region}} = \frac{Number\ of\ Graduates\ in\ region\ X_i}{Total\ Number\ of\ Graduates\ in\ all\ regions} \quad \textbf{(1)}$$

The second step of the employed methodology focuses on the calculation of *Human Capital Stock* in each of the selected regions, based on the number of persons aged 25-35 years in 2021 with tertiary education (as well as the corresponding information expressed per 10,000 persons in each region). In turn, a *Stock of Human Capital index* that measures each region's share to the total number (i.e. of all regions) of persons aged 25-34 years with tertiary education can be calculated as follows:

$$\textbf{\textit{Stock of Human Capital index of } } \boldsymbol{X_i} \textbf{\textit{ region}} = \frac{Number\ of\ persons\ aged\ 25\text{–}34\ with\ tertiary\ education\ in\ 2021\ in\ region\ X_i}{Total\ Number\ of\ persons\ aged\ 25\text{–}34\ years\ in\ 2021\ with\ tertiary\ education\ in\ all\ regions} \quad \textbf{(2)}$$

Then, dividing equation (*2*) (i.e. *Stock of Human Capital Index*) to equation (*1*) (i.e. *Production of Human Capital Index*), an overall index for the brain drain performance in each region can be calculated as the ratio of *region's X_i share to the total number of graduates of ISCED 5 to 8 level in all regions in 2016*, divided by *region's X_i share to the total number of persons aged 25-34 years with tertiary education in 2021 in all regions*, defined as follows:

$$\textbf{\textit{Brain Drain Ratio}} = \frac{Region's\ Xi\ share\ to\ the\ total\ number\ of\ graduates\ of\ ISCED\ 5\ to\ 8\ level\ in\ all\ regions\ in\ 2016}{Region's\ Xi\ share\ to\ the\ total\ number\ of\ persons\ aged\ 25{-}34\ with\ tertiary\ education\ in\ all\ regions\ in\ 2021} \quad \textbf{(3)}$$

If the calculated value for the above-defined Brain Drain Ration exceeds the value of 1, this means that the region has more stock of human capital, compared to what it produces, which, in turn, indicates that it is a brain drain region. Similarly, if the calculated Brain Drain Ratio takes a value less than 1, this indicates that the region is a brain drain region, as it has less stock of human capital, compared to what it produces.

2.3. Data

To examine the performance of European cities in terms of Human Capital Production, data from the European Tertiary Education Register (ETER) database was used, which is the reference dataset on European Higher Education Institutions (HEIs). ETER collects data on nearly 3,500 HEIs over the period 2011-2019 providing descriptive information, geographical information, students and graduates, personnel etc. Most data are collected from National Statistical Authorities (NSAs) or ministries of participating countries and are subject to extensive checks and harmonization.[3] The ETER dataset is widely used in the scholarly literature on higher education and science policy, as well as for policy reports and analyses (Lepori et al. 2023). For the purpose of the estimation of the brain drain ratio, the estimation of the human capital production index (that is the numerator of this ratio) is based on ETER data for 2016. The investigation of the human stock index is based on data obtained from Eurostat regarding the number of persons aged 25 to 34 years for 2019 and it is collected at

[3] The development of ETER has been funded by the European Commission and is part of the current efforts to establish a European Higher Education Sector Observatory; it is closely connected to the establishment of a broader data infrastructure in the field of science and innovation studies (RISIS).

NUTS-2 level. As the information of the human capital stock index (the denominator of the brain drain ratio) refers to NUTS-2 level, the corresponding information for the human capital production index was also reported to NUTS-2 level -hence the reference unit of the analysis of the brain drain outcomes is at NUTS-2 level. Having excluded 48 NUTS-2 regions, for which the number of graduates per 10,000 is less than 250, the final sample of the analysis consists of 182 NUTS-2 regions.

2.4. Empirical Findings

This section presents the findings of the empirical analysis, providing evidence aiming at: i) Mapping the European University Cities (city level); ii) Portraying the Graduates Map at NUTS-3 level; iii) Classifying EU regions according to their brain drain outcomes; and iv) Identifying the brain drain regions at NUTS-3 level.

i. Mapping the European University Cities

Aiming at capturing as recent a picture of Human Capital Production as possible, data were collected at the Higher Education Institution level for 2019 for 26 European Union countries (for Slovenia, data for 2019 were not available from the ETER database). To this end, Table 1 presents the Number of University Cities (812 in total) for the 26 European countries. Germany displays the highest value of University cities (179), followed by Italy (97). France (71) and Poland (70) are ranked at the third and the fourth place correspondingly, Spain follows with 48 University cities, while the rest of the countries have less than 40 University cities. Map 1 portrays, in more detail, the European map of the number of Higher Education Institutions at NUTS-3 level.

Table 1: Number of University Cities in each MS, 2019

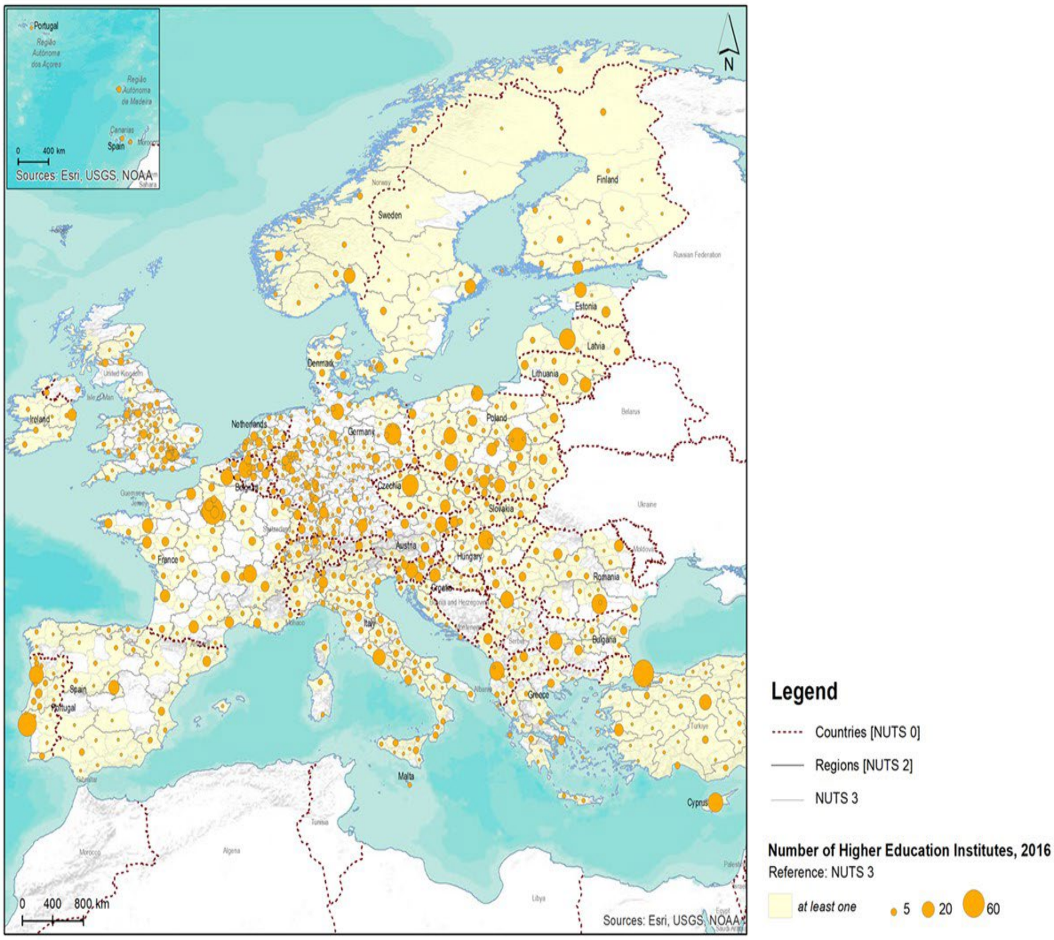
DE	179	**AT**	20
IT	97	**FI**	20
FR	71	**HU**	20
PL	48	**BG**	15
ES	48	**SK**	15
PT	38	**IE**	13
NL	28	**RO**	13
EL	27	**LV**	9
SE	23	**LT**	8
DK	22	**CY**	5

BE	21	**MT**	4
CZ	21	**EE**	3
HR	21	**LU**	1
Total (N=812)			

Source: Analysis of ETER database.

Note: There were no available data for Slovenia in the ETER database for 2019.

Map 1: Number of Higher Education Institutions at NUTS-3 level

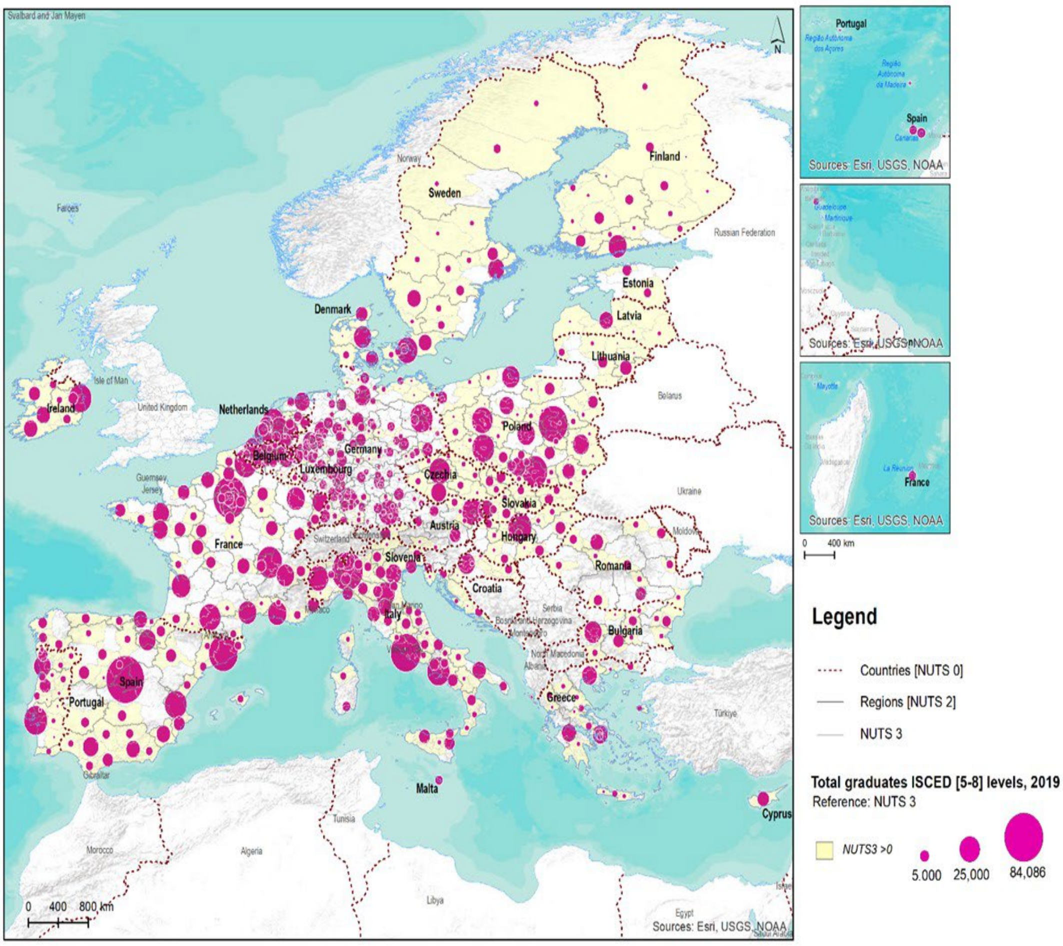


Source: Analysis of ETER database.

ii. *Portraying the Graduates Map at NUTS-3 level*

In this section, the focus turns to the examination of European cities and regions in terms of their potential in Human Capital Production. Map 2 shows the number of graduates in the year 2019 (in absolute terms) of ISCED education levels 5-8 at the level of NUTS-3 regions. Map 2 captures where human capital is produced in Europe, but it has an inherent weakness: large numbers in human capital production are expected to occur in large (in terms of population concentration) areas. Put differently, Map 2 shows that the production of human capital is greater in areas with large population size, but does not tell us why this might be the case: is this because areas with large populations are more efficient at producing human capital, or because they simply have a larger population and therefore proportionally higher production of human capital than areas with smaller population sizes?

Map 2: Number of Graduates [ISCED 5-8 level] at NUTS-3 level, 2019



Source: Analysis of ETER database.

One way to make the performance of regions with different population sizes comparable is to convert information on human capital production from absolute to relative terms. This means, instead of presenting the absolute number of graduates of a region in 2019, to express this information in relative terms, i.e. as the number of graduates per 1000 inhabitants. Information on the number of graduates expressed in relative terms ensures comparability across regions, allowing the following question to be examined: does the size of a region matter for its performance in terms of human capital production? To address the above question, the 635 NUTS-3 regions of the sample are classified into 3 categories based on their population size: i) small regions (i.e. regions with less than 0.05% of the sum of the population of the 635 regions); ii) medium sized regions (i.e. regions with 0.05% to 0.15% of the sum of the population of the 635 regions); and iii) large regions (i.e. regions with more than 0.15% of the sum of the population of the 635 regions). Attempting a -by naked eye- analysis Table 2 presents the mean value of the number of graduates per 1,000 inhabitants in 2019 for each population size category. The estimated figures suggest that the population size of a region does not appear to be closely associated with its human production capability, as the mean value of number of graduates per 1,000 inhabitants does not differ significantly across the three population size categories (it is 12.6 graduates for the small regions; 8.1 Graduates for the medium sized regions; and 10.2 for the category of the large, according to their population size, regions).

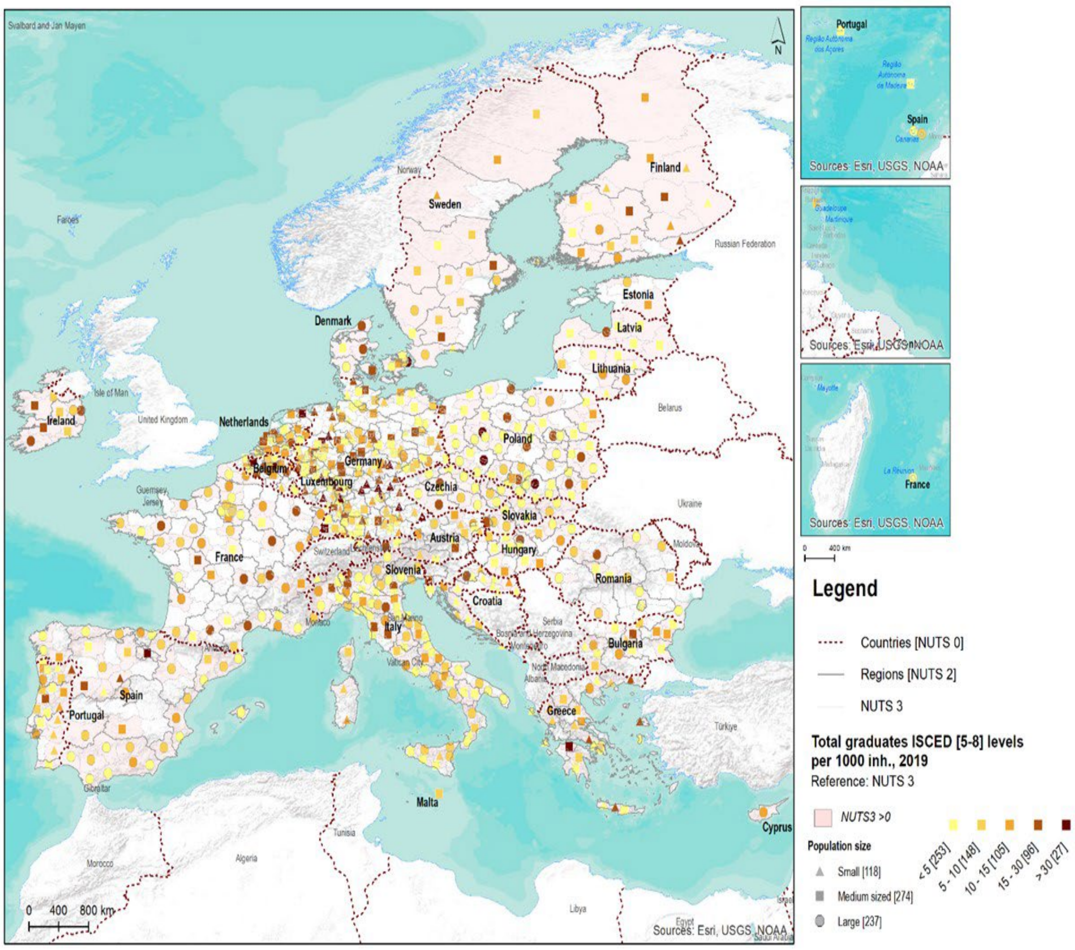
Table 2: Region's human capital production by broader categories of region's population size

Region's population size categories	Number of NUTS-3 University regions	Number of Graduates (ISCED 5-8) in 2019	Number of Graduates (ISCED 5-8) per 1,000 inhabitants in 2019
with less than 0.05% of the total population* (small regions)	103	144,495	12.6
with 0.05% to 0.15% of the total population (medium sized regions)	278	688,453	8.1
with more than 0.15% of the total population (large regions)	254	2,432,954	10.2
Total	**635**	**3,265,902**	**9.8**

Source: Analysis of ETER database (for the number of graduates) & Eurostat's da (for population size).
Note: * total population refers to the total population of the 365 regions.

The absence of any strong relationship between region's population size and its capability regarding the production of human capital is presented in more detail in Map 3, which portrays the number of graduates per 1,000 inhabitants for regions of different size. Dark shadows stand for higher number of human capital production, while the shape of the symbol (i.e. triangle, square of cycle) stand for the population size (small, medium sized and large regions, respectively). The emerging picture suggests that in a number of countries medium-sized regions appear to be those who exhibit the highest number of graduates per 1,000 inhabitants in 2019. This becomes particularly evident in South European countries (Greece and Spain are the most prominent examples) but also in the Nordic (Sweden and Finland), as well as in many Continental countries (with Germany and the Netherlands being the most remarkable examples of this case).

Map 3: Number of Graduates [ISCED 5-8 level] at NUTS-3 level per 1000 inhabitants, by region's population size, 2019

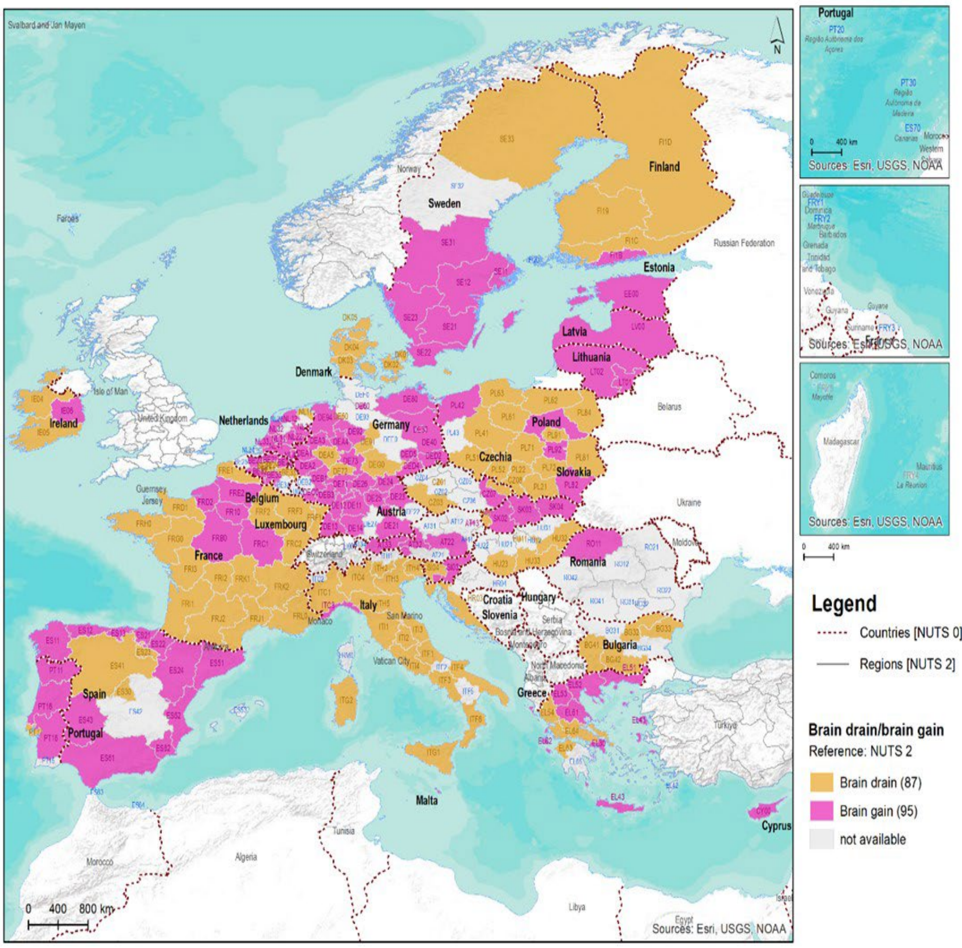


Source: Analysis of ETER database (for the number of graduates) & Eurostat's data (for population size).

iii. Classifying EU regions according to their brain drain outcomes

Having examined each region's *Human Capital Production index* (based on the share of each region to the total number of graduates in 2016 of all the selected regions) and the *Human Capital Stock* index (based on the share of each region to the total number of persons aged 25-34 with tertiary education of all the selected regions), a brain drain index has been estimated as the ratio of the *Human Capital Production index* divided by the *Human Capital Stock* index. The analysis has been carried out at NUTS-2 level. A value less than 1 indicates that the region is a brain drain region, while a value greater than 1 suggests that the region is a brain gainer. Map 4 portrays the findings of the analysis mapping with orange colour the brain drain regions and with pink the brain gainers.

Map 4: Brain drain and brain gain NUTS-2 level regions, 2019



Source: Analysis of ETER database (for the number of graduates) & Eurostat's data (for the number of persons aged 25-34 with tertiary education).

Trying to summarise the findings presented in Map 4 to cluster, it seems as a first group of countries consisted of Bulgaria, Denmark and Hungary stand for the "*pure brain drain countries"*, as almost all of their NUTS-2 regions appear to be classified as brain drain regions. As "*mainly brain drain countries"* appear to be the Czech Republic, Finland, France, Italy and Poland. On the other hand, the vast majority of the regions in Belgium, Germany, Spain, the Netherlands, Portugal, Sweden and Slovakia appear to be classified as *brain gain* regions. As "*brain gain countries*" are also classified Latvia, Lithuania, Estonia, Cyprus, Malta and Romania. Finally, in Greece, Slovenia, Croatia and Ireland the emerging picture appears to be rather mixed as within each of these countries there are rather balanced outcomes as regards the number of brain drain and the brain gain regions.

iv. Identifying the brain drain regions at NUTS-2 level

The last sub-section of the empirical analysis present the detailed list of the brain drain regions according to the employed methodology. To ease the presentation brain drain regions are classified to five sub-groups based on their ranking according to the estimated brain drain ratio, as follows:[4]

- The most brain drain regions (ranked in place 1 to 15) (see Table 3)
- Relatively brain drain regions (ranked in place 16 to 30) (see Table 4)
- Middle-ranked brain drain regions (ranked in place 31 to 45) (see Table 5)
- Relatively low brain drain regions (ranked in place 46 to 60) (see Table 6)
- The least brain drain regions (ranked 61 to 76) (see Table 7)

The estimated brain drain ratio (presented in the fifth column of each of the following tables) has to be examined in conjunction with the place that each region is ranked in the human capital stock and the human capital production rankings (presented in columns six and seven of the following tables). This is because some regions could be classified as brain drain regions simply because there are top (or very good) performers as regards their production of human capital -and obviously there is not capacity to keep all these graduates. In this case, brain brain is mainly due to the fact that these regions produce too much human capital, rather than of their structural

[4] In addition, Table A3 in the Appendix presents seven cases of brain drain regions (for those countries that there is no brain drain region) in order to identify the relative more eligible region in these countries that the next steps of the analysis of the Endorse project should focus on.

weaknesses or other characteristics that lowers their ability to attack (or retain) human capital.[5]

Table 3: The most brain drain regions (ranked 1 to 15)

rank	Country	NUTS-2	N2_LABEL	Brain Drain Ratio	Rank in Human Capital Stock	Rank in Human Capital Production
1	ES	ES23	La Rioja	0.250	69	1
2	SK	SK01	Bratislavsky kraj	0.364	22	2
3	CZ	CZ03	Jihozapad	0.371	164	10
4	BE	BE31	Prov. Brabant wallon	0.478	21	4
5	GR	EL63	Dytiki Ellada	0.479	104	13
6	HR	HR05	Grad Zagreb	0.516	41	6
7	NL	NL11	Groningen	0.543	28	8
8	PL	PL91	Warszawski stoleczny	0.546	4.5	3
9	PL	PL41	Wielkopolskie	0.547	145	22
10	IT	ITI4	Lazio	0.553	147	36
11	BG	BG32	Severen tsentralen	0.556	139	20
12	DK	DK05	Nordjylland	0.560	84	17
13	GR	EL54	Ipeiros	0.566	117	26
14	SI	SI04	Zahodna Slovenija	0.582	37	7
15	IT	ITF1	Abruzzo	0.607	156	54

Source: Analysis of ETER database (for the number of graduates) & Eurostat's data (for the number of persons aged 25-34 with tertiary education).

Table 4: Relatively brain drain regions (ranked 16 to 30)

rank	Country	NUTS-2	N2_LABEL	Brain Drain Ratio	Rank in Human Capital Stock	Rank in Human Capital Production
16	PL	PL21	Malopolskie	0.614	47	9
17	BG	BG33	Severoiztochen	0.614	170.5	57
18	CZ	CZ01	Praha	0.621	13	5
19	IT	ITF3	Campania	0.630	178	94
20	FR	FRK1	Auvergne	0.656	78	28
21	PL	PL71	Lodzkie	0.663	127	40
22	FR	FRJ1	Languedoc-Roussillon	0.667	73	24
23	FI	FI1D	Pohjois- ja Itae-Suomi	0.683	124	46

[5] A prominent example of this case is the region La Rioja (ES23).

24	PL	PL63	Pomorskie	0.705	94	33
25	PL	PL51	Dolnoslaskie	0.713	50	15
26	DK	DK04	Midtjylland	0.721	48	23
27	FI	FI1C	Etelae-Suomi	0.721	122	53
28	FR	FRI3	Poitou-Charentes	0.729	93	45
29	BE	BE24	Prov. Vlaams-Brabant	0.735	15	12
30	DK	DK03	Syddanmark	0.746	95	49

Source: Analysis of ETER database (for the number of graduates) & Eurostat's data (for the number of persons aged 25-34 with tertiary education).

Table 5: Middle-ranked brain drain regions (ranked 31 to 45)

rank	Country	NUTS-2	N2_LABEL	Brain Drain Ratio	Rank in Human Capital Stock	Rank in Human Capital Production
31	IT	ITI3	Marche	0.746	152	75
32	IT	ITH5	Emilia-Romagna	0.749	136.5	61
33	IT	ITC4	Lombardia	0.754	153	78
34	FR	FRH0	Bretagne	0.754	51	32
35	PL	PL61	Kujawsko-Pomorskie	0.756	118	50
36	FR	FRC2	Franche-Comte	0.762	111	60
37	FI	FI19	Laensi-Suomi	0.764	107.5	55
38	IT	ITI1	Toscana	0.764	162	86
39	PL	PL81	Lubelskie	0.771	97.5	42
40	IE	IE05	Southern	0.781	11.5	16
41	ES	ES41	Castilla y Leon	0.787	62	37
42	PL	PL62	Warminsko-Mazurskie	0.791	167	90
43	DE	DE72	Giessen	0.796	115	64
44	IT	ITH2	Provincia Autonoma di Trento	0.803	151	88
45	DE	DE50	Bremen	0.803	146	77

Source: Analysis of ETER database (for the number of graduates) & Eurostat's data (for the number of persons aged 25-34 with tertiary education).

Table 6: Relatively low brain drain regions (ranked 46 to 60)

rank	Country	NUTS-2	N2_LABEL	Brain Drain Ratio	Rank in Human Capital Stock	Rank in Human Capital Production
46	HU	HU11	Budapest	0.806	9.5	11
47	FR	FRF3	Lorraine	0.807	74	43
48	BE	BE10	Region de Bruxelles-Capitale	0.818	20	14

49	FR	FRD1	Basse-Normandie	0.820	109.5	68
50	HU	HU33	Del-Alfoeld	0.831	181.5	153
51	PL	PL72	Swietokrzyskie	0.832	128	66
52	IT	ITG2	Sardegna	0.833	183	158
53	BG	BG41	Yugozapaden	0.834	59	31
54	IT	ITC1	Piemonte	0.836	165	114
55	FR	FRE1	Nord-Pas-de-Calais	0.837	77	56
56	FR	FRJ2	Midi-Pyrenees	0.839	25	27
57	SE	SE33	Oevre Norrland	0.839	55	41
58	HU	HU23	Del-Dunantul	0.847	176	140
59	BG	BG42	Yuzhen tsentralen	0.849	173	120
60	FR	FRF1	Alsace	0.850	39	35

Source: Analysis of ETER database (for the number of graduates) & Eurostat's data (for the number of persons aged 25-34 with tertiary education).

Table 7: The least brain drain regions (ranked 61 to 76)

rank	**Country**	**NUTS-2**	**N2_LABEL**	**Brain Drain Ratio**	**Rank in Human Capital Stock**	**Rank in Human Capital Production**
61	IT	ITG1	Sicilia	0.862	184	171
62	DK	DK02	Sjaelland	0.864	150	101
63	PL	PL52	Opolskie	0.865	157	92
64	IE	IE04	Northern and Western	0.875	17	25
65	FR	FRK2	Rhone-Alpes	0.877	24	30
66	FR	FRI2	Limousin	0.881	53	51
67	DE	DEA5	Arnsberg	0.881	159.5	117
68	FR	FRI1	Aquitaine	0.884	56	48
69	IT	ITH4	Friuli-Venezia Giulia	0.888	155	118
70	FR	FRL0	Provence-Alpes-Cote d'Azur	0.891	54	44
71	PL	PL84	Podlaskie	0.899	121	70
72	PT	PT17	Area Metropolitana de Lisboa	0.923	29	39
73	IT	ITF6	Calabria	0.944	181.5	167
74	HR	HR03	Jadranska Hrvatska	0.954	135	98
75	IT	ITI2	Umbria	0.955	142	106
76	FR	FRG0	Pays-de-la-Loire	0.958	46	58

3. Classifying brain drain regions in the EU according to their socio-economic performance

3.1. Literature Review on the Role of HEIs for Regional Development

Having universities close at hand benefits a region economically, socially, and culturally. Research has shown that despite experiencing population loss, which is an inherent phenomenon in many developed countries, endogenous growth is possible through innovation, the attraction of new businesses to modern industries and cluster building (Bartholomae & Schoenberg, 2019). Higher educational institutes (HEIs) can contribute significantly to these goals by providing human capital in the form of students, graduates and researchers to the community and building bridges to local firms and authorities. In the past decades, the academic and political focus had been set on direct economic impacts through the commercialization of knowledge but more recently, the perception moved gradually towards integrated approaches and softer means of influence on the society (OECD, 2017). However, some critics warn against too much interference from HEIs and fear for its independency and integrity (Krimsky, 1991 as cited in Etzkowitz et al., 2000).

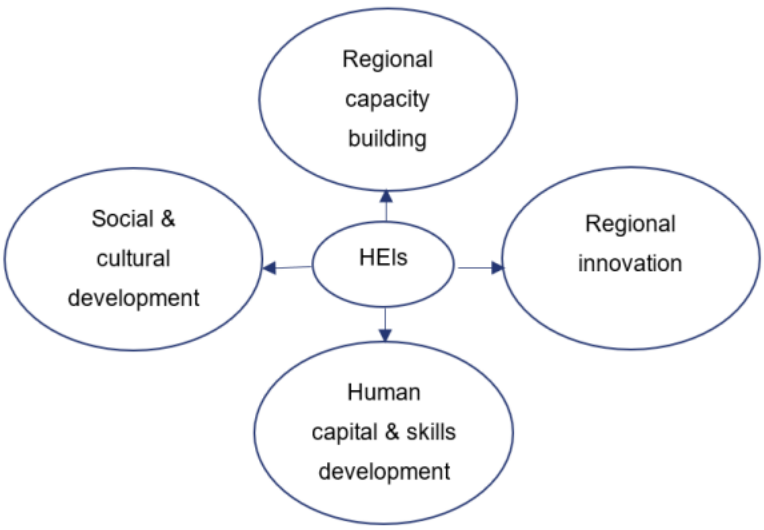
Given that the distribution of human capital is a main predictor of income and wellbeing in modern economies (Corcoran & Faggian, 2017), universities are increasingly engaged with the attraction and retention of talent, which is a clearly formulated goal of regional policy (European Union, 2011). Understanding graduates' location choices helps a region to prevent or mitigate consequences of a loss of knowledge, technology transfer, investment, and trade (Corcoran & Faggian, 2017, p.1-2). As far as motives for graduate migration are concerned, literature often identifies socio-economic characteristics such as job opportunities, the affordability and availability of housing, the availability of infrastructure, leisure activities and health care as well as labour market conditions and access to information regarding all mentioned points as key factors for success (European Committee of the Regions, 2018).

Many links exist between universities and their surrounding regions, some very direct and material, others subtle and harder to quantify (Power & Malmberg, 2008). The latter are the ones easily overlooked by policymakers although their impact is potentially more sustainable. Yet, it is tempting to invest into projects with a clearly measurable rate of success. In addition, developing programs for non-tangible spheres of influence is far more challenging. Nevertheless, in recent years, the EU has recognized the importance of holistic systems for regional development and increasingly moved away from one-sided, ephemeral project financing (European Union, 2011).

Most plainly, universities have a direct economic impact on their region as being big employers and purchasers of various local goods and services. Besides, they attract people to the region – students, professionals, tourists – as well as project funding (EU, 2011; Power & Malmberg, 2008). This contribution is rather passive, because universities cause multiplier effects simply by conducting their core business, research and teaching, without paying special effort to regional engagement. However, in the past decades, HEIs have been attributed a much broader scope of influence that goes beyond monetary effects and requires an active engagement with local communities. Furthermore, not only technological studies but also Arts, Humanities and Social Sciences are now in the center of attention (EU, 2011).

In its 2007 report "Higher Education in Regions: Globally Competitive, Locally Engaged" the OECD identifies four pillars of regional progress: regional capacity building, regional innovation, human capital and skills development and social and cultural development, which are also the areas the EU focuses on.

Figure 2: The four Dimensions of University-Induced Growth according to the OECD



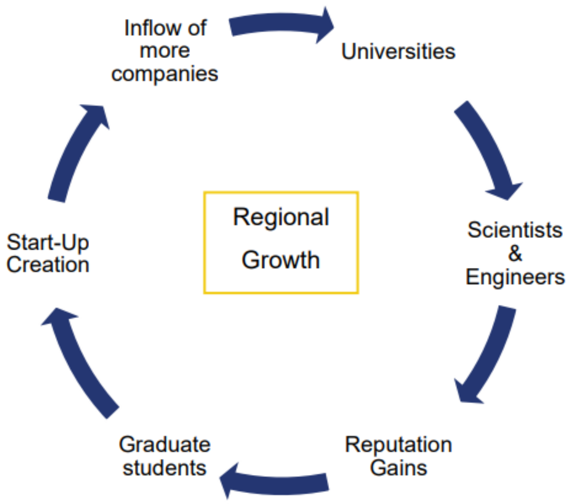
Source: by the authors, modified after European Union (2011) and OECD (2017)

The RIS University concept involves HEIs tailoring their activities to meet regional needs and fostering strong local networks. Innovation is critical for economic growth, contributing to over 50% of economic performance in developed countries from 1970-1995 (Simmie, Sennett, Wood & Hart, 2002). HEIs connect with local businesses through consultancy services, innovation vouchers, and knowledge transfer partnerships to drive regional development. However, the success of such initiatives varies, with mixed results reported in different. Science parks and research centers also play a vital role by facilitating collaboration between businesses and universities (European Union, 2011).

Regional capacity building involves HEIs in activities that support their region's entrepreneurial climate through graduate enterprise development, internships in local SMEs, and aiding students in starting their own businesses by providing essential resources. University spin-outs, where new entities are formed from university-developed assets, play a crucial role. Effective coordination between HEIs, public, and private sectors is essential to avoid isolating student start-ups (European Union, 2011). HEIs also facilitate network and cluster development, enhancing regional returns by fostering inter-firm collaborations, though a critical mass of related businesses and effective regional governance are prerequisites (European Union, 2011; OECD, 2017). Geographic proximity to HEIs positively influences intellectual property development through knowledge spillovers, evidenced by increased patent production (European Union, 2011; Agrawal, 2001).

Florida (1999) criticizes policies overly focused on commercializing academic knowledge, advocating instead for HEIs to attract global talent, which he argues will have a greater economic impact through a "self-reinforcing cycle of growth."

Figure 3: Florida's self-enforcing Cycle of Growth



Source: by the authors, based on Florida (1999)

The OECD supports this view, emphasizing the importance of "knowledge transfer on legs" for regional development and labour markets (OECD, 2017). HEIs act as "talent magnets," fostering regional clusters by attracting students, senior scientists, and industry pioneers. However, there is a risk of losing developed human capital to other regions (Betts & Lee, 2005). HEIs should align programs with local industry needs to help regions develop key sectors, although predicting future needs is challenging. Talent retention and attraction policies, such as tax benefits and career development schemes, are crucial to mitigating the outflow of skilled individuals from university towns (European Union, 2011).

Engaged universities furthermore actively contribute to their communities, leveraging their resources for societal benefit by educating future citizens whose decisions as consumers, workers, and entrepreneurs drive societal change (Goddard, Kempton & Vallance, 2013). HEIs engage with local communities through student volunteering programs that address societal issues, raise awareness, and enhance the university's appeal in a competitive education market. Broader initiatives aim to increase educational participation among underrepresented groups, though addressing social exclusion requires broader governmental intervention (European Union, 2011). HEIs also promote cultural development through partnerships with museums, galleries, and theaters, contributing to regional growth by fostering a "creative class" (Florida, 2003). Critics argue these cultural activities benefit only a small elite (European Union, 2011). Universities can also shape regional branding, with institutions like Bologna, Heidelberg, Uppsala, Oxford, and Cambridge enhancing regional identity and driving economic spillover effects (Power & Malmberg, 2008).

3.2. Methodology

Subsequently, in part B of the analysis, multi-dimensional socio-economic indicators are added to the identified NUTS2 and NUTS3 regions affected by brain drain, and the concerned regions are clustered into groups to identify similarities and recognize patterns. The choice of socio-economic indicators for the analysis corresponds to the factors associated with brain drain and brain gain.

A composite indicator was chosen for the analysis because it allows for a comparison of regions using a wide array of separate indicators. The composite indicator combines individual indicators into a single index based on a theoretical framework that determines the selection and weighting of the variables (OECD, 2013). Commonly, it is used for multi-dimensional concepts that cannot be expressed in a single indicator, e.g., competitiveness, industrialization, sustainability, etc. and measures benchmarking performance (OECD, 2008, p. 13).

There are advantages and disadvantages in using indicators and the discussion whether they are good or bad per se is ongoing. The OECD argues that while indicators help identifying trends and monitoring performance over time, they can also send misleading policy implications when poorly constructed. Moreover, while summarizing complex, multidimensional realities does facilitate interpretation and the conversion of results to the public (citizens, media) and policy makers, it may also invite to draw too simplistic policy conclusions. In addition, the construction of the indicator demands “craftsmanship” of the modeler as the selection and weighting of indicators must be made carefully and should be transparent to ensure accountability. Some scholars see value in combining indicators to a summary statistic while others prefer to look at the set of indicators chosen individually and not aggregate them (OECD, 2008, p. 13-14). The steps for constructing a composite indicator can be summarized as follows:

Figure 4: Ten steps of constructing a composite indicator

1. Theoretical Framework
- Basis for selection and combination of indicators in a meaningful way

2. Data Selection
- Based on measurability, geographical coverage, relevance and relationship
- Proxy variables where data is scarce

3. Inputation of Missing Data
- Different approaches of imputation should be considered
- Checking for outliers

4. Multivariate Analysis
- Assessing the suitability of data
- Explanation of methodological choices

5. Normalization
- Normalizing the data for comparability
- Dealing with extreme values and skewed data

6. Weighting and Aggregation
- According to the underlying framework
- Correlation of indicators needs to be considered and treated correctly

7. Robustness and Sensitivity
- Robustness in terms of the included indicators, normalization method, imputation of missing data, weighting choices and aggreagation method

8. Back to the Real Data
- Transparency
- Decomposition into the underlying indicators or values

9. Links to other Variables
- Correlation to other published indicators
- Identifying linkages

10. Presentation and Visualization
- Different ways of presentation and visualization influence interpretation

Source: by the authors, based on OECD (2008)

Indicators are aggregated based on actors that shape the regional development, in particular people, firms and policymakers. Each of these disposes of different means of influence, and each has unique interests. Thus, indicators were selected and grouped according to the dimensions Human Capital, Industry, and Government.

3.3. Data

Data for the socio-economic indicator was collected from the general and regional statistics in Eurostat, whereby the availability of data narrowed the options. The year 2019 was chosen as reference year because data was widely available for this year in all indicators. Where it was not, the values were imputed with a compound annual growth rate conducted with the values from previous, available years. In case of boundary changes, most often between NUTS 2016 and NUTS 2021 in Belgium, Croatia, and Italy[6] (Eurostat, n.d.), either the average was used in case of a merge of two regions or the compound annual growth rate of the old region(s) to get the 2019 value of the new region(s). Supplement data regarding the poverty rate was furthermore derived from national statistical offices from Belgium, Finland, and France because those countries were missing in the Eurostat data. Likewise, data regarding the enterprise growth rate were missing for Belgium, Germany and Slovenia and added from national statistics as well.

Table 8 provides an overview of the chosen indicators:

[6] Belgium: NUTS 3 regions of BE32 modified (2 suppressed, 2 newly created, 4 boundary changes)
Croatia: one region (HR03) discontinued, three new created; NUTS 3 regions of ex-HR03 rearranged to newly created NUTS 2 regions
Estonia: EE006 and EE007 recoded into EE009 and EE00A (boundary changes)
Italy: Sardinia (ITG2) rearranged: 4 regions discontinued, 4 with boundary changes, 1 newly created

Table 8: Overview of Variables in the Composite Indicator

Dimension	*Indicator*	*Source(s)*	*Geographic level*	*Reference year(s)*	*Best value*
Human Capital	Household Income	Eurostat: NAMA_10R_2HHINC	NUTS 2	2019	highest
Human Capital	Median Age	Eurostat: DEMO_R_PJANIND3	NUTS 3	2019	lowest
Human Capital	Net Migration	Eurostat: DEMO_R_GIND3	NUTS 3	2019	highest
Human Capital	Poverty Rate	Eurostat: ILC_PEPS11 Belgium: STATBEL - AROP; Finland: StatFin - 131y; France: Insee - Series of Poverty Rate	NUTS 2	2019 (France: 2015)	lowest
Human Capital	Tertiary Education of Working Population	Eurostat: EDAT_LFSE_04	NUTS 2	2019	highest
Human Capital	Youth Employment	Eurostat: EDAT_LFSE_33	NUTS 2	2019	Highest
Industry	Enterprise Growth Rate	Eurostat: BD_SIZE_R3 Belgium: STATBEL - Number of active enterprises subject to VAT according to economic activity and employer class; Germany: RDB - 52111 Unternehmensregister-System; Slovenia: SiStat – 1418806S	NUTS 3	2018-2019	highest
Industry	GDP/capita	Eurostat: NAMA_10R_3GDP	NUTS 3	2019	Highest
Industry	Economic Diversity	Eurostat: NAMA_10R_3GVA	NUTS 3	2019	highest
Industry	Gross Fixed Capital Formation	NAMA_10R_2GFCF (Capital) NAMA_10R_2GDP (GDP)	NUTS 2	2019	highest
Industry	Persons employed in Science & Technology	HRST_ST_RCAT	NUTS 2	2019	Highest
Industry	Productivity	NAMA_10R_3GVA (GVA)	NUTS 3	2019	Highest

		NAMA_10R_3EMPERS (Employment)			
Government	Economic Resilience	LFST_R_LFE2EMP	NUTS 2	2019-2020	Highest
Government	Gender Employment Gap	LFST_R_LFE2EMP	NUTS 2	2019	Lowest
Government	Infant Mortality	DEMO_R_MINFIND	NUTS 2	2019	Lowest
Government	Population Density	DEMO_R_D3DENS	NUTS 3	2019	Highest
Government	Taxes on Income & Wealth	NAMA_10R_2HHINC (Taxes), DEMO_R_D2JAN (Population)	NUTS 2	2019	Lowest
Government	Tourism Arrivals	TOUR_OCC_ARN2 (Arrivals), DEMO_R_D2JAN (Population)	NUTS 2	2019	Highest

Source: by the authors

Some of the indicators had to be adjusted for comparability reasons, e.g., by setting absolute numbers in relation to GDP, employees, or inhabitants, others were created newly.

Household Income per inhabitant (Eurostat, 2022i) is the balance of the primary net incomes/national income households dispose of and is assumed to be negatively correlated with brain drain for higher income prospects serve as a pull factor to a region.

The **Median Age** (Eurostat, 2022j) on the other hand is expected to positively correlate with it as a lower median age indicates a younger population, thus more people of working age and younger cohorts that will join in the future. This increases the attractiveness both for firms looking for employees and for young graduates who like to be among peers for settling or staying in the region.

The crude rate of **Net Migration** (Eurostat, 2022d) depicts the percentage difference between in- and outmigration and is assumed to be negatively correlated to brain drain for there is evidence from literature and empirical studies that migrants move to regions that offer more favorable socio-economic conditions relative to the predominant ones at home.

For the same reason, a high **Poverty Rate** is assumed to act as a push factor. “People at risk of poverty or social exclusion” (Eurostat, 2022k), a main indicator of the European Union Statistics on income and living conditions (EU-SILC) was utilized. It does not only reflect a household’s level of income but includes unemployment, a low work intensity, working status and several other socio-economic characteristics. To determine the share of people at risk of poverty or social inclusion, persons which fulfill at least one of the three conditions (which are own indicators in Eurostat respectively) are counted: the person is at risk of poverty if its income is below the at-risk of-poverty threshold; the person suffers from severe material and social deprivation if it lacks at least seven out of thirteen items desirable or necessary for an adequate quality of life and/or the person is living in a household with a very low work intensity, i.e. where adults worked less than 20% of their combined potential during the previous year (Eurostat, 2021). Data for Belgium, France and Finland was added from the respective national statistical offices.

The share of People with **Tertiary Education** (ISCED levels 5-8) in the working population (Eurostat, 2022l) is supposed to increase a region’s attractiveness for the concomitant creation of highly skilled human capital, innovation stimuli, and productivity gains that literature predicts.

The **Youth Employment rate** (Eurostat, 2022m) reports the share of employed people aged 15 to 34 years of the total amount of people in this age group that are neither in education nor training. It was deemed an important indicator for economic prosperity. In addition, job and career prospects are named the most crucial element shaping the location decision of highly skilled migrants in literature.

Table 9 provides a statistical overview of the indicators in the human capital dimension.

Table 9: Descriptive statistics of the human capital indicators

	Household Income	Median Age	Net Migration	Poverty Rate	Tertiary Education	Youth Employment
Unit	Million €	Year	Percent	Percent	Percent	Percent
Min	3,300	25.9	-15.8	7.9	11.7	32.7
Max	33,800	53.6	37.9	49.7	55.5	89.9
Median	14,200	44.0	0.5	18.6	28.8	76.1
Mean	15,478	44.27	1.6	21.1	29.5	74.6
Standard Deviation	7,180.6	3.8	5.7	9.0	9.2	10.7
Variance	51,561,113	14.3	32.6	81.4	84.6	114.9

Source: by the authors

Economic Diversity is a self-calculated indicator. It is based on the indicator "Gross value added at basic prices by NUTS 3 regions" (Eurostat, 2022n) that depicts the GVA by various industries. GVA measures the sum of the gross value added through the production of goods and services (output at basic prices minus intermediate consumption at purchaser prices) in the individual sectors and distinguishes itself from GDP insofar as it includes the financial intermediation services indirectly measured (FISIM) in the sector, which is a separate position in the national accounts. FISIM are payments for services provided by intermediaries to the customers and could be charges or interest margins. Moreover, GVA is net of taxes (minus subsidies) while they are included in the GDP (European Central Bank, 2003).

First, the share of the GVA added by the distinct industries[7] was divided by the total GVA achieved in the region. Subsequently, the number of industries that accounted

[7] Agriculture, forestry, and fishing [A], Industry (except construction) [B-E], Construction [F], Wholesale and retail trade; transport; accommodation and food service activities; information and communication [G-J], Financial and insurance activities; real estate activities; professional, scientific

for over 10% of the total GVA was counted. The notion behind is that economic diversity, i.e., a high number of significant industries being active in a region is assumed to contribute to its attractiveness and makes it resilient to economic shocks in a particular sector.

The **Enterprise Growth Rate** is self-calculated as well, based on the Business demography statistics (Eurostat, 2022o) and measures the percentage difference in the absolute number of active enterprises in a region between 2018 and 2019. It serves as proxy for entrepreneurial activity that manifests itself amongst others in the number of newly founded enterprises per year. The business demography statistics includes other indicators that would have been suitable such as the enterprise birth rate, the enterprise death rate, and the churn rate (the sum of the aforementioned rates), however these indicators lack data for 20 out of 27 EU member states. Data from for this analysis relevant countries Belgium, Germany and Slovenia was added from the respective national statistical authorities.

GDP per capita (Eurostat, 2022p) is the main indicator for measuring economic development and is assumed to be negatively correlated with brain drain.

Gross Fixed Capital Formation (Eurostat, 2022q) depicts investments, deducting disposals, in fixed assets during a given period. Fixed assets are tangible or non-tangible production outcomes that are used repeatedly or continuously for a minimum of one year (Eurostat, 2019). For comparability reasons they have been set in relation to regional GDP. Investments are crucial for enterprise growth and if used properly, contribute to economic development.

The indicator **Persons employed in Science & Technology** in percentage of the total population (Eurostat, 2022r) is a proxy for the availability of highly skilled human capital in a region. Highly skilled human capital is the backbone of modern economies and for many firms the most important input factor in the production process. From literature it is known that firms, in particular when operating in certain industries, tend to locate in close proximity to it.

Productivity, measured as GVA per Employee, is a proxy for the quality of the local workforce that a firm can dispose of. It was calculated by dividing the GVA achieved in

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and technical activities; administrative and support service activities [K-N], Public administration and defence; compulsory social security; education; human health and social work activities; arts, entertainment and recreation, repair of household goods and other services [O-U] the regions (Eurostat, 2022n) by employment figures (in thousand persons) (Eurostat, 2022s). A higher productivity is assumed to attract firms to a region.

Table 10 provides a statistical overview of the indicators in the industry dimension.

Table 10: Descriptive statistics of the industry indicators

	GDP per capita	Capital Formation	Economic Diversity	Enterprise Growth	Persons in S&T	Productivity
Unit	€ per inhabitant	Percent of GDP	GVA per industry > 10%	Percent	Percent of total population	GVA in million € per 1,000 employees
Min	4,000	0.14	1	- 0.16	9.3	8.3
Max	191,900	0.41	6	0.68	37.9	162.2
Median	21,500	0.20	4.0	0.03	18.2	50.3
Mean	23,335	0.21	3.9	0.03	18.7	47.3
Standard Deviation	14,971.9	0.04	0.5	0.05	5.1	21.6
Variance	224,158,652	0.0014	0.234	0.002	26.24	465.74

Source: by the author

Economic Resilience is a self-constructed indicator that depicts the shift in employment levels (Eurostat, 2022t) from 2019 to 2020, measured as percent change of total figures. If the employment level did not much worsen before and after the start of the COVID-19 pandemic and first lockdowns it is assumed that the region is resilient to economic shocks.

The **Gender Employment Gap** was used instead of the more common indicator Gender Pay Gap because data on wages is not split by gender on the regional level in Eurostat, but employment figures are (Eurostat, 2022t). It was calculated as the difference between male and female employment (the number of male employees minus the number of female employees, divided by the number of male employees) and serves as proxy for gender equality. The indicator was chosen in line with findings from the literature review that women tend to be more mobile than men and seek employment in regions that offer them equal employment and career opportunities.

As proxy for the quality of the health care system the **Infant Mortality Rate** (Eurostat, 2022u) was chosen, as other indicators (e.g., hospital beds, number of doctors and health care personnel, etc.) are incomplete because they do not cover all the countries incorporated in this analysis. The risk of infant mortality can be reduced by prenatal care, treatments that help reduce the risk of preterm birth and low birth weight, newborn screenings, and other treatments (United States Department of Health and Human Services, 2021). Therefore, there are strong grounds for linking the infant mortality rate to the availability and access to adequate medical healthcare which is a factor potentially considered in migrant's location choice.

Population Density (Eurostat, 2022v) is assumed to be negatively correlated to brain drain as evidence points to the fact that highly skilled migrants like to locate in densely populated metropolitan areas (European Committee of the Regions, 2018, p. 10) because there they can capitalize on skills more easily than in sparsely populated areas.

Taxes on Income & Wealth (Eurostat, 2022i) impact household's disposable income and should not be disproportionately high to avoid offsetting financial moving benefits of high skilled migrants or triggering local graduates to seek employment elsewhere. In fact, tax benefits are a tool suggested by the European Union (2011, p. 27) to attract and retain talent, which is why taxes on income and wealth are assumed to be positively correlated with brain drain. For comparability reasons, the rate has been set in relation to population (Eurostat, 2022h).

Tourism Arrivals (Eurostat, 2022w) report the annual number of tourists in a region staying at hotels, holiday and other short-stay accommodation, camping grounds, recreational vehicle parks and trailer parks. The indicator, which has been set in relation to population (Eurostat, 2022h), serves as a proxy for the availability of infrastructure, because other indicators directly linked to transport such as the number of kilometers per thousand square kilometers of road, rail and navigable inland waterway networks do not cover all the countries incorporated in this analysis. Infrastructure facilitates travelling and commuting to workplaces farther away and is therefore negatively correlated to brain drain.

Table 11 provides a statistical overview of the indicators in the government dimension.

Table 11: Descriptive statistics of the government indicators

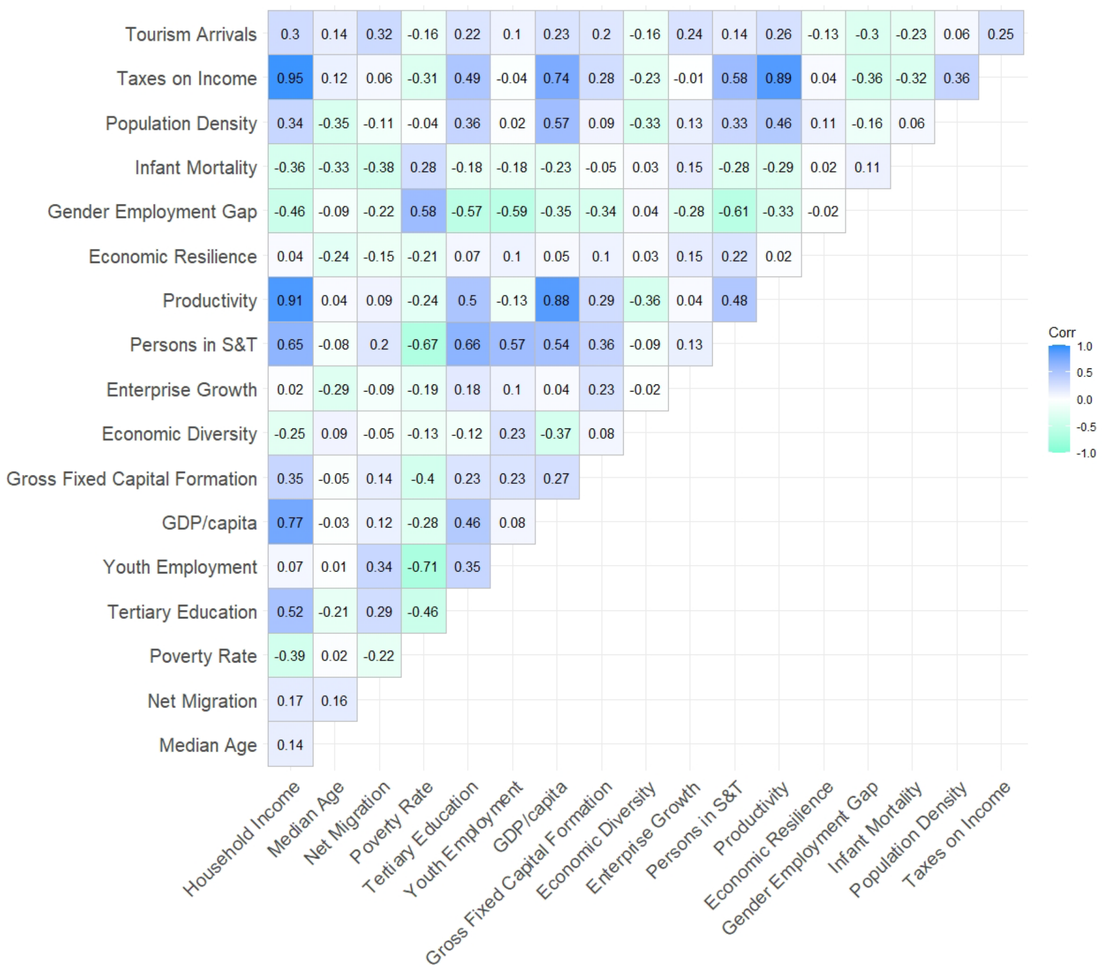
	Economic Resilience	Gender Employment Gap	Infant Mortality	Population Density	Taxes on Income & Wealth	Tourism Arrivals
Unit	Percent	Percent	Percent	Percent	Million € per inhabitant	Tourists per inhabitant
Min	- 0.13	- 0.19	1.0	1.0	0.0002	0.3
Max	0.07	0.44	9.7	9,456.8	0.007	12.3

Median	- 0.014	0.15	3.1	113.5	0.0018	1.7
Mean	- 0.015	0.15	3.3	433.9	0.0021	2.1
Standard Deviation	0.019	0.10	1.3	1,270.5	0.0015	1.8
Variance	0.0003	0.011	1.634	1,614,043	0.000002	3.29

Source: by the authors

The fourth step is a multivariate analysis that investigates the overall structure of the chosen data and assesses whether it is suitable and sufficient to describe the observed phenomenon (OECD, 2008, p. 25-26). For this purpose, the interrelation between a set of variables is depicted in a correlation matrix. Correlations, however, do not necessarily represent the real influence of a variable on the observed phenomenon (OECD, 2008, p. 26), and almost always some correlation between the various indicators in one dimension that will be subsequently aggregated, can be observed.

Figure 5: Correlation Matrix



Source: by the authors

Despite some observable higher correlation between certain indicators, they are considered to measure different facets of regional attractiveness and thus, remain in the indicator.

As the individual indicators have different measuring units, the data needs to be normalized to allow for comparison and aggregation. Different normalization methods exist, each comes with advantages and disadvantages and the selection of a suitable method is a crucial step in the construction of the composite indicator. For this analysis, the Min-Max Normalization was deemed to serve the objective of the indicator best which sorts the observations into an identical range between 0 (worst) and 1 (best). Attention must be paid to extreme values and outliers which could distort the indicator. However, the benefit of this method is that it widens the range of indicators within a small interval, thereby increasing the effect on the composite indicator more than other statistical methods (OECD, 2008, p. 28). The Min-Max method is not stable when further data, for example for the following year, is added and minimum and maximum values consequently change. In this case, the composite indicator must be re-calculated (OECD, 2008, p. 85).

For positive indicators, where the higher the value the better the ranking (e.g., Household Income, Youth Employment, Productivity), the difference between an individual observation x within an indicator j and the minimum value in this indicator is divided by the range of the maximum value Max (x_j) and the minimum value Min (x_j) (formula 1).

$$\text{Index value of } x_j = \frac{x_j - \text{Min}\,(x_j)}{\text{Max}\,(x_j) - \text{Min}\,(x_j)} \qquad (1)$$

For negative indicators, where the lower the value the better the ranking (e.g., Median Age, Poverty Rate, Infant Mortality) the difference between the maximum value Max (x_j) and the individual observation x is divided by the range of the maximum value Max (x_j) and the minimum value Min (x_j) (formula 2).

$$\text{Index Value of } x_j = \frac{\text{Max}\,(x_j) - x_j}{\text{Max}\,(x_j) - \text{Min}\,(x_j)} \qquad (2)$$

In a next step, indicators are weighted and aggregated. Various weighting techniques, derived from statistical models, exist and the chosen technique can have a significant effect on the composite indicator. In most cases however, equal weighting is deployed, i.e., all indicators are given the same weight with the reasoning that the variables contribute equally to the observed phenomenon. Equal weighing was also chosen for the composite indicator in this analysis. It should be considered that equal weighting in a composite indictor that consists of variables grouped into dimensions, can give higher weight to the dimension that groups the larger number of variables (OECD, 2008, p. 31). This has been taken into account in the construction of the composite indicator by choosing an equal number of indicators per dimension.

Like weighting techniques, aggregation methods also vary. While a linear aggregation rewards base-indicators proportionately to the chosen weights, a geometric aggregation rewards those countries/regions with higher scores. In both methods, a deficit in one indictor can be offset by a surplus in another indicator in the same dimension, however in the linear aggregation the compensability is constant while in the geometric aggregation, compensability is lower for those indicators with low values. This implies that a country/region which scores badly in one indicator needs to achieve much better results in the others to improve when the geometric aggregation is used. In some policy scenarios, modelers may decide against the possibility of compensation when very different indicators are used, and a high sore, for instance in an environmental indicator shall not be able to offset a low score in a social indicator. In this case, other approaches must be deployed (OECD, 2008, p. 32-33). For the composite indicator in this analysis, both the linear and the geometric aggregation had been used, which yielded similar results. This was done to test for robustness.

3.4. Empirical Findings

This section presents the findings of the empirical analysis, providing evidence aiming at: i) Evaluating the overall socio-economic performance of these brain drain regions and ii) Categorizing them based on the dimensions of Human Capital, Industry and Government. The latter is quite important as it shows in which regions should the next steps of the ENDORSE project has to focus on, by investigating the characteristics and the entrepreneurial capacity in these regions.

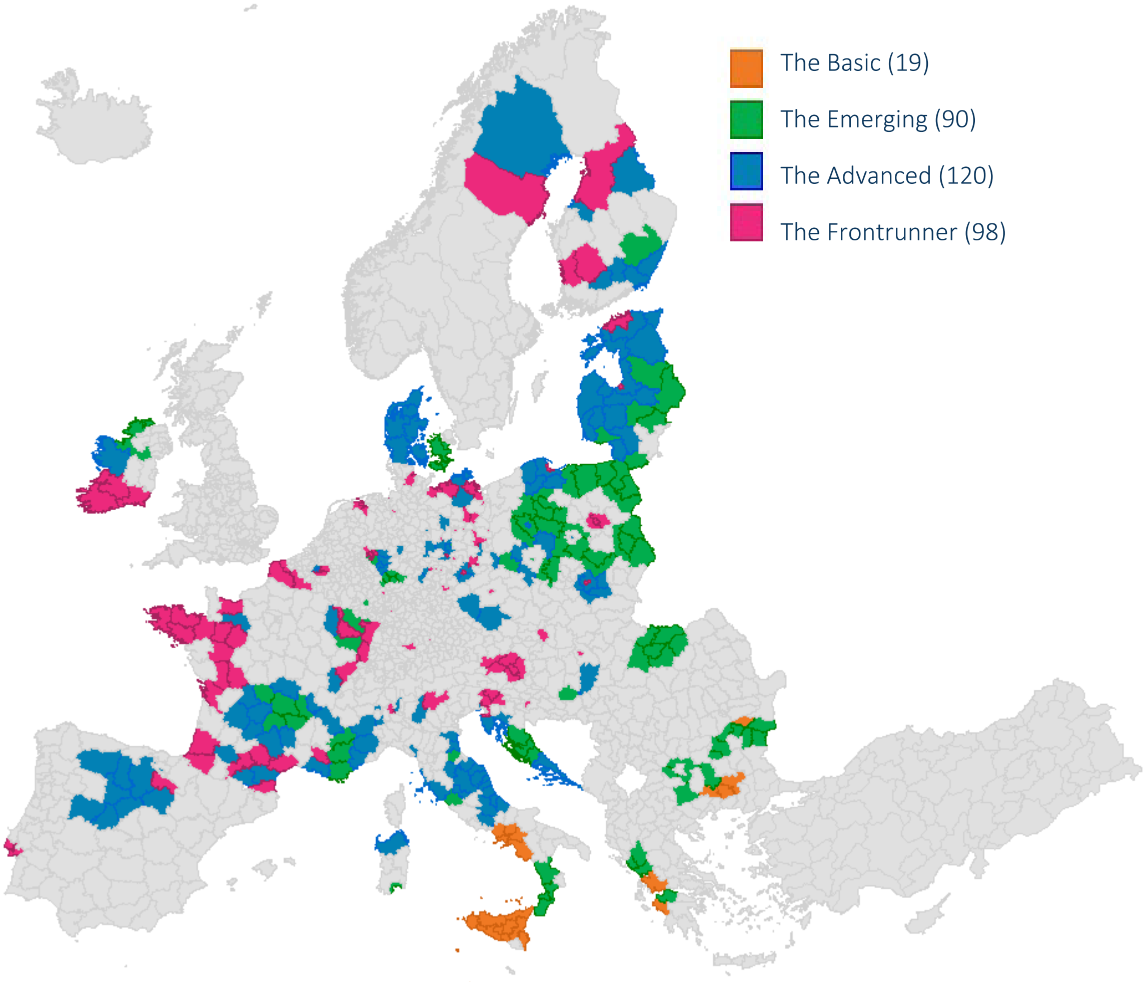
i. Evaluating the overall socio-economic performance of brain drain regions

The outcome of the constructed composite indicator is the Socio-Economic Performance Index which ranks all regions affected by brain drain from the countries included in the analysis according to their socio-economic performance. Results decomposed in the three subdimensions Human Capital, Industry and Government are included as well. Moreover, the struggling regions were clustered based on similarities to see which ones fall within the same group and what characteristics they have in common, to subsequently draw conclusions on the prevalent socio-economic problems. The clustering was done via geovisualization, applying natural breaks maps. A natural breaks map uses a nonlinear algorithm that groups observations in a way that the homogeneity within the group is maximized. In other words, break points are determined that yield groups with the largest internal similarity (Anselin, 2020). The maps depict NUTS 3 regions to comply with the smallest available geographical level in the socio-economic indicators. In total, there are 327 NUTS-3 regions. For indicators where data was only available on NUTS 2 level, the NUTS 2-value had been assigned to all corresponding NUTS-3 regions.

The Socio-economic Performance Index depicts the overall result of the composite indicator and ranks regions according to their socio-economic performance from 1 (best) to 327 (worst). Despite all regions being affected by population loss, they differ largely in their achieved score, and on a scale from 0 to 1 rank between 0.04 (Caltanissetta, Sicilia, Italy) to 0.513 (Prague, Czech Republic) in the geometric mean. However, even the best performers achieve little more than half of the possible score, hence yielding merely mediocre results.

The natural breaks map in figure 3 groups regions based on their achieved geometric mean. Regions in light grey are undefined, meaning they do not have a corresponding value, either because the country was not included in the analysis, the region does not have a university, or the region was not affected by brain drain. The analyzed regions are colored in shades of blue according on the cluster they have been allocated to. The darker the color, the higher the performance rank. The visualization clearly demonstrates the uneven degree of socio-economic performance amongst European regions, across and within country borders.

Figure 6: Mapping the Socio-Economic Performance Index



Source: by the authors

ii. Categorizing brain drain regions based on the dimensions of Human Capital, Industry and Government

The four lowest-ranked regions, **The Basic**, exhibit a low geometric score of under 0.084 and contain four regions in Central Bulgaria, two regions in Greece and 13 regions in Southern Italy. These are regions on the periphery, which are among the poorest in Europe.

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Table 12: Basic Regions

Country	No. of regions	Areas
Bulgaria	4	Central Bulgaria
Greece	2	Western Greece
Italy	13	Sicilia & Campania (Southern Italy)

Source: by the authors

In this category, we find smaller cities in proximity of rural areas that cover local and regional demand for tertiary education. These cities are experiencing problems related to socioeconomic (unemployment, lack of technological progress, poverty, social exclusion), demographic (population loss, aging) and physical factors (poor infrastructure and housing). Most of these regions have an agricultural tradition with a low industry mix and low accessibility. Their economic development is below average and while offering education opportunities in proximity for households with no other access to education, they do not provide any opportunities for their graduates than to leave. Universities in these regions don not just struggle to retain graduates but also to attract students which limits the universities contribution to the local economy as well.

The second cluster, **The Emerging**, comprises 90 regions that achieved scores between 0.086 and 0.226. These regions have been called emerging regions and are geographically widespread, although a lot of them are in the periphery as well.

Table 13: Emerging Regions

Country	No. of regions	Areas
Bulgaria	11	All of Bulgaria, including the capital Sofia & coastal city Varna
Croatia	3	Coastal region incl. city Zadar
Germany	11	Arnsberg, Gießen & Dessau in Sachsen-Anhalt
Denmark	2	NUTS2 region Sjælland (island, excl. Kopenhagen)
Finland	1	Etelä-Savo, South-Eastern Finland
France	10	Central & Southern France
Greece	4	Western Greece & Ipeiros (bordering Albania)
Hungary	1	Baranya in Southern Hungary incl. Pécs
Ireland	1	Border region

Italy	7	Island Sardegna, Calabria (South), Emilia-Romagna (North, incl. Bologna), Lazio (region surrounding Rome)
Latvia	2	Latgale (Eastern Latvia), Vidzeme (Northeastern)
Lithuania	4	NUTS2 region Vidurio ir vakarų Lietuvos regionas (without capital)
Poland	27	All over Poland
Romania	6	NUTS 2 region Nord-Vest

Source: by the authors

These regions comprise cities, mostly peripheric, with low population density and tradition in agriculture and/or specific areas of manufacturing (clothing, leather, furniture etc.). The relocation and polarization of economic activities caused by the globalization in the last decades has led in these cities to a failure to carry out the shift from traditional manufacturing to innovation-driven industries and modern business-oriented services. This affected the economic power of urban areas and deteriorated the fiscal base of cities, leading to financial bottlenecks impeding the maintenance of local infrastructure levels and deteriorating quality of life. As a result, the challenges related to vacant and underutilized housing, uncompetitive, old local businesses, as well as a poor infrastructure have rapidly emerged. Universities were matched to the industries located in these regions and are residuals of a past industrial structure. Sometimes, universities are purposely located in these regions to contribute to urban growth.

With 120 individual regions assigned to it, the third cluster, **The Advanced**, is the largest, and also exhibits the largest rank distance among the four categories, with scores ranging from 0.226 to 0.315.

Table 14: Advanced Regions

Country	No. of regions	Areas
Belgium	2	Brussels and Arrondissement of Halle-Vilvoorde, the district surrounding Brussels
Czech Republic	2	Southern Bohemia, city Plzeň
Germany	22	NUTS 2 regions Arnsberg, Braunschweig, Chemnitz, Sachsen-Anhalt, Detmold, Brandenburg, Thüringen, Dresden & Mecklenburg-Vorpommern
Denmark	5	NUTS 2 regions Midtjylland, Nordjylland & Southern Denmark (all regions except Sjælland, that is in the 3rd cluster and

		Hovedstaden, which is the capital region and not a brain drainer)
Estonia	4	All regions except Põhja-Eesti (which is in the 1st cluster)
Spain	8	NUTS 2 regions Castilla y León in Northwestern Spain (plateau surrounded by mountains)
Finland	6	NUTS 2 regions Pohjois- ja Itä-Suomi (North and East Finland) and Etelä-Suomi (South Finland incl. Turku)
France	17	geographically covering all of France
Croatia	4	Jadranska Hrvatska incl. cities Split and Dubrovnik (Adriatic Coast)
Hungary	1	Bács-Kiskun in Southern Hungary, south of Budapest
Ireland	1	West Ireland incl. city Galway
Italy	25	Northern and Middle Italy
Lithuania	5	NUTS2 region Vidurio ir vakarų Lietuvos regionas (without capital)
Latvia	3	Kurzeme (north of Riga), Zemgale (south of Riga), Pierīga (the region surrounding Riga)
Poland	14	Geographically covering all Poland (incl. Lodz, Gdansk, Krakow, Poznan)
Sweden	1	Norrbottens län, Northern Sweden

Source: by the authors

In contrast to the first two categories, a lot of bigger cities or smaller cities in metropolitan areas that do face structural problems and low industrial diversity, can be found here. These cities benefit to a certain extent from agglomeration effects or positive spillover effects from bigger cities in their proximity. However, due to low flexibility and risk-aversity these cities do lack innovative performance and economic growth. Their problems are induced by multidimensional aspects such as changes in socio-spatial structures, changes in labor market flexibility, financial deepening, the increase of the skill premium caused by technological progress as well as deindustrialization. Consequently, some of these cities appear to be suffering from the lock-in effects caused by the path dependence, which is determined by traditional socioeconomic structure, less-speedy industrial evolution, and inefficient production practices. Universities are an organic part of the urban infrastructure and very often one of the most important contributors to local development. Also, their reputation allows them to attract national and international students.

Lastly, 98 regions are categorized as **The Frontrunners** with a corresponding geometric rank of over 0.316. This cluster accommodates mainly metropoles and regions surrounding them, such as the capital cities Prague, Riga, Zagreb, Bratislava and Bucharest and the regions surrounding the Polish capital Warsaw.

Table 15: Frontrunner Regions

Country	No. of regions	Areas
Austria	6	Styria
Belgium	2	Arrondissement of Nivelles (south of Brussels), Arrondissement of Leuven (east of Brussels)
Czech Republic	1	Prague
Germany	36	NUTS2 regions Arnsberg, Brandenburg, Münster, Oberfranken, Mecklenburg-Vorpommern, Dresden, Thüringen, Chemnitz, Sachsen-Anhalt, Karlsruhe
Estonia	1	Põhja-Eesti (incl. Tallinn)
Spain	1	La Rioja (Northern Spain)
Finland	3	Pohjois- ja Itä-Suomi, Länsi-Suomi (incl. Tampere)
France	25	Geographically covering all of France
Croatia	1	Zagreb
Hungary	1	Budapest
Ireland	3	Mid-West (incl. Limerick) and South-West (incl. Cork, Kerry)
Italy	2	Lombardia (incl. Milano), Trentino-Alto Adige/Südtirol
Latvia	1	Riga
Netherlands	3	Groningen
Poland	5	Trójmiejski, Miasto Kraków, Warszawski wschodni, Warszawski zachodni (regions surrounding Warsaw), Miasto Warszawa
Portugal	1	Área Metropolitana de Lisboa
Sweden	1	Västerbottens län
Slovenia	4	Obalno-kraška, Gorenjska, Osrednjeslovenska (incl. capital Ljubljana and cities Portoroz and Bled), Goriška
Slovakia	1	Bratislava

Source: by the authors

These cities and regions experience a certain level of economic dynamism, sectoral heterogeneity, involvement in global production processes, R&D investment, and human capital. However, the cities sometimes lack certain types of important social capital such as accessibility shortcomings of firms' R&D cooperation with local research institutes and universities, missing knowledge transfers and personal exchange between firms. In some cases, these cities are so called consumer cities that focus on culture, art, tourism, and research but in many cases low entrepreneurial success. Universities are well known and attract many national and international students without having a matching labor market. Graduates are being pulled by regions with better opportunities. Amongst these cities are also capital cities in eastern Europe that despite economic growth compete with regions abroad that are more attractive to graduates.

4. Discussion

This report has presented a methodology for measuring human capital flows across European regions and cities, utilizing indices to estimate the human capital production and stock of each region. By calculating a brain drain ratio based on these indices, the study determined whether regions are experiencing brain drain or brain gain in a manner that is comparable across NUTS-2 European regions. The analysis provided valuable insights, including the mapping of European University Cities, the distribution of graduates at NUTS-3 level in 2019, the classification of EU regions by brain drain outcomes, and the identification of brain drain regions at NUTS-2 level, which will be the focus of future project steps.

The empirical evidence underscores the significant dispersion of human capital utilization index (HUI) across the EU, highlighting the role of Higher Education Institutions (HEIs) and higher education opportunities in reshuffling the young population across different areas. Medium and small university cities, which attract a substantial proportion of students, could act as catalysts for improving the age structure of localities. However, the retention rate and long-term engagement of graduates in their locations of graduation are uneven across cities and regions, pointing to the crucial influence of local labor markets and entrepreneurial activities.

Further analysis in this report revealed the intricate relationship between socio-economic performance and brain drain in university regions across the EU-27. The use of a composite indicator offered a nuanced understanding of regional disparities, particularly highlighting the challenges faced by regions in Southern and Eastern Europe. Although regions in Western, Northern, and Central Europe perform better, they still exhibit significant differences between metropolitan and non-metropolitan areas.

The insights from this study highlight the need for targeted policy interventions to improve socio-economic indicators in struggling regions. These findings will inform the development of region-specific educational materials aimed at enhancing students' entrepreneurial capabilities. By providing practical information on local industries, skill requirements, funding sources, and business initiation processes, the project seeks to empower students to contribute to their region’s economic resilience and growth.

The university regions have been categorized into four types, each with unique characteristics and challenges, for which specific educational materials have been developed. This initiative aims to mitigate brain drain by fostering a new generation of entrepreneurs equipped with the knowledge and resources to thrive within their own regions, promoting balanced and equitable development across the European Union.

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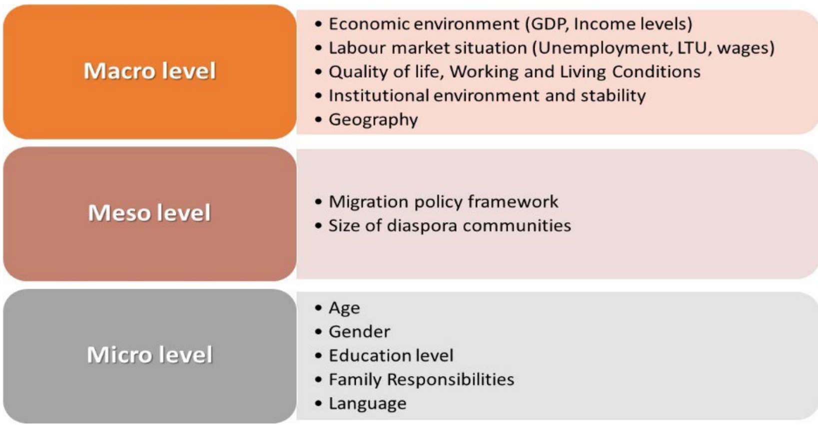
APPENDIX

Figure A1. Factors behind the individual migration decisions of skilled workers



Source: ICF, 2018

Table A1. Interpreting variables of high-skilled migration "Brain Drain"

FACTOR	INTERPRETING VARIABLE	PUSH/PULL FACTOR	REFERENCE
ECONOMIC CONDITIONS	Economic liberalization	Pull factor	Tzeng, 2006
	GDP, Income levels	Push/pull factor	ICF, 2018
	"Death" of enterprises	Push factor	ESPON, 2017
	The world-wide expansion of the information technology (IT) sector	Pull factor	Saxenian, 2002
	Mismatch of demand and supply of skilled labor	Push factor	Perrou, Savvaidou, 2019
	Active economic growth, higher per capita wealth	Pull factor	Cavallini, et al., 2018
	Sector-specific strengths	Pull factor	Cavallini, et al., 2018
	The development of Knowledge economy (economy based on the production, distribution and the use of knowledge information (OECD, 1996) • Presence of knowledge intensive sectors (E.G. high-tech manufacturing and services; financial and business services; health; education; creative and cultural services), • Establishment of high level scientific institutions, • Presence of high educational level of the population and the work force, Investments in innovation at firm, individual and sector level • Economy with linkages in scientific functions • Economy able to obtain knowledge from other economies through cooperation and networking •	Pull factor	ESPON, 2018, Brinkley, Lee, 2007

LABOUR MARKET CONDITIONS	Unemployment, wages, working conditions.	Push/pull factor	ICF, 2018
	Bad working conditions	Push factor	Widuto, 2019
	High unemployment, low wages among young people	Push factor	ESPON, 2017
	Higher employment rates, types of available job opportunities, higher wages, easier access to labour market (time of being out of employment after graduation)	Pull factor	Cavallini, et al., 2018
	High youth unemployment	Push factor	Boc, 2020
	Mismatch of demand and supply of skilled labour	Push factor	Perrou, Savvaidou, 2019
	Duration of job seeking, characteristics of job contract (starting salary, fixed-term or permanent etc.,)	Push factor	Boc, 2019
	Job offers, high salaries,	Pull factor	Jaeger, Kreutzer, 2012
SOCIAL CONDITIONS	Social inequality, difference in earnings	Push factor	Luts et al., 2019
	Inability to access minimal levels of civic participation	Push factor	Boc, 2020
	Size of diaspora communities	Pull factor	ICF, 2018
	Increase of social security contributions	Push factor	Boc, 2019
	Robust social security	Pull factor	Cavallini, et al., 2018
	Linguistic similarities	Pull factor	Cavallini, et al., 2018
	Cultural similarities	Pull factor	Cavallini, et al., 2018
	Social inclusion (high share of foreign inhabitants)	Pull factor	Cavallini, et al., 2018
	Faculty of Graduation	Push/pull factor	Jaeger, Kreutzer, 2012

BUSINESS ENVIRONMENT	Administrative barriers	Push factor	ESPON, 2017
	Institutional environment	Push factor	ICF, 2018
	Severe taxation	Push factor	Boc, 2019
	A well-established knowledge economy	Pull factor	Cavallini, et al., 2018
	Support services for business development	Pull factor	Brain Flow Project, n.d.,
	Existence of entrepreneurial network connections	Pull factor	Jaeger, Kreutzer, 2012
	Close distance to universities that favours the establishment of students' spi-offs and business start-ups	Pull factor	Jaeger, Kreutzer, 2012
	The development of Knowledge economy (economy based on the production, distribution and the use of knowledge information)	Pull factor	ESPON, 2018
	Good connectivity among businesses and universities	Pull factor	Boc, 2020
	Planned infrastructure for foreign companies to relocate or to form in this area	Pull factor	Boc, 2019
POLITICAL CONDITIONS	Political liberalization	Pull factor	Tzeng, 2006
	Corruption in the country	Push/pull factor	Boc, 2019
	Bad political environment	Push factor	ESPON, 2017
	Uncertainty	Push factor	Boc, 2019
AMENITIES	Reputation of better education system	Pull factor	Cavallini, et al., 2018
	Quality of the educational system	Push/pull factor	Grecu, Titan, 2016
	Quality of the overall infrastructure	Push/pull factor	Grecu, Titan, 2016

	Quality of the education system, availability of infrastructure, leisure activities, social life (gastronomy, creative economy)	Pull factor	Brain Flow Project, n.d.,
	Availability and accessibility of information to the talent targeted, Availability and accessibility of local services that welcome and facilitate the relocation of attracted labour	Pull factor	Brain Flow Project, n.d.,
	Physical and technological infrastructure, quality education system, cultural activities, medical care system	Pull factor	Boc, 2020
PUBLIC POLICY	Migration policy framework	Pull factor	ICF, 2018
	Migration policy	Pull factor	Ray, 2012
GEOGRAPHICAL LOCATION	Being in the European Periphery	Push factor	Cavallini, et al., 2018
LIVING CONDITIONS	Quality of life	Push/pull factor	ICF, 2018
	Inability to access minimal levels of life quality	Push factor	Boc, 2020
	Bad quality of life	Push factor	Widuto, 2019
	Much better quality of life	Pull factor	Cavallini, et al., 2018
	Life expectancy	Push/pull factor	Grecu, Titan, 2016
	Affordability and availability of housing, cost of living, health care system	Pull factor	Brain Flow Project, n.d.,
IMAGE OF THE REGION	Positive foreign perception, planning and implementation of city branding strategies	Pull factor	Brain Flow Project, n.d.,

Table A3: Seven cases of brain drain regions (for those countries that there is no brain drain region)

rank	Country	NUTS-2	N2_LABEL	Brain Drain Ratio	Rank in Human Capital Stock	Rank in Human Capital Production
77	AT	AT22	Steiermark	**1.194**	103	122
78	LV	LV00	Latvija	**1.212**	68	74
79	LT	LT02	Vidurio ir vakaru Lietuvos regionas	**1.418**	44	110
80	EE	EE00	Eesti	**1.343**	76	108
81	RO	RO11	Nord-Vest	**1.092**	177	170
82	CY	CY00	Kypros	**1.671**	166	100
83	MT	MT00	Malta	**1.567**	79	146