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ORIGINAL RESEARCH

Analyzing countries' performances within the international student mobility program over time

Kristijan Breznik[1,2] · **Marialuisa Restaino**[3] · **Maria Prosperina Vitale**[4] · **Giancarlo Ragozini**[5]

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Abstract

The phenomenon of internationalization is a priority for higher education institutions. The Erasmus program is the cornerstone of their internationalization strategy, bringing benefits for student recruitment and career outcomes, as well as for staff expertise. Within this scenario, our contribution aims to analyze the performance of European education systems in terms of learning mobility between countries from a longitudinal perspective. International student mobility is analyzed in the context of the Erasmus programs over twelve years in order to compare international mobility trajectories between European countries in terms of quantitative benchmarking and to identify the factors that may influence a country's performance in terms of its role in mobility network exchanges. A mixed analytical strategy of analysis was adopted, combining exploratory and confirmatory approaches from a network perspective. Centrality indices and network modeling are computed to compare countries' performances and factors affecting mobility patterns in higher education systems. The main findings can offer policy suggestions for universities in order to improve the quality of their international services.

Keywords International student mobility · Data-driven network · University attractiveness indicators · Network modeling · Erasmus service evaluation

✉ Maria Prosperina Vitale
mvitale@unisa.it

Kristijan Breznik
kristijan.breznik@mfdps.si

Marialuisa Restaino
mlrestaino@unisa.it

Giancarlo Ragozini
giragoz@unina.it

[1] International School for Social and Business Studies, Celje, Slovenia

[2] Faculty of Environment Protection, Velenje, Slovenia

[3] Department of Economics and Statistics, University of Salerno, Fisciano, Salerno, Italy

[4] Department of Political and Social Studies, University of Salerno, Fisciano, Salerno, Italy

[5] Department of Political Sciences, University of Naples Federico II, Napoli, Italy

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1 Introduction

Tertiary (also called higher or university) education systems are one of the main contributors to the development, socio-economic progress, and competitiveness of countries (Volchik et al., 2018). Evaluating their performance is one of the main issues for governments and education authorities (Stumbriene et al., 2020). In recent years, the relevance of globalization and internationalization processes has increased the need for data-driven performance analysis to guide policy makers' decisions (Tavares et al., 2022), to promote changes in higher education policies and to decide on the investments in tertiary education (Volchik et al., 2018).

The performance analysis of education systems has been widely researched from different perspectives through several methodological approaches and at different levels, from the individual to the country and cross-country perspectives. In the context of operational research, the Data Envelopment Analysis–DEA, is often used together with the development of composite indicators (Bougnol & DulDulá 2006; Camanho et al., 2023). Different indicators are, indeed, considered to offer a big picture of multidimensional aspects to be taken into account when comparing countries (Stumbriene et al., 2020).

Under this scenario, the European Commission (EC) has been monitoring the performance of Member States' education policies in line with the *Education and Training* 2020 (ET2020) strategic framework since 2009. Common objectives and target indicators are set out to achieve convergence in the performance of EU education systems. The main objective is, among others, to promote global learning mobility. As Stumbriene et al. (2020) note, *"at least 20% of higher education graduates and 6% of 18–34-year-olds with an initial vocational qualification should have spent some time studying or training abroad"*. In 2018, 9.11% of graduates in the EU-27 had a temporary experience abroad in terms of credit mobility in university contexts.[1]

The EU Council recently identified five priorities to be addressed in the framework of the Strategic Framework for European Cooperation in Education and Training (2021–2030), one of which is related to the realization of lifelong learning and mobility for all.[2]

Several European initiatives can promote learning and teaching mobility in order to enhance personal development and reinforce cooperation between educational institutions. More specifically, Erasmus programs[3] represent the backbone of Higher Education Institutions (HEI) internationalization strategy, as they benefit students' competences and careers, as well as the acquisition of expertise and new teaching skills for staff (European Commission (EC), 2014). They represent the most relevant mobility experiment the EU has developed to promote the exchange of educational and professional experiences among countries. However, efforts must continue to ensure a balance in the mobility flows. Cross-national data are still not available for the measure of learning mobility (Flisi et al., 2014) and the EU Member States have adopted a target which cannot be fully computed due to the unavailability of information from some non-EU countries.

In this context, our study aims at analyzing the performance of European education systems in terms of learning mobility across countries from a longitudinal perspective. International

[1] For details see https://op.europa.eu/webpub/eac/education-and-training-monitor-2020/en/chapters/chapter2.html#ch2-7.

[2] For details see "Council Resolution on a strategic framework for European cooperation in education and training towards the European Education Area and beyond (2021–2030) 2021/C 66/01", https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32021G0226(01).

[3] The Erasmus program is usually used as a synonym of the general mobility policy of the European Commission. In the following, the Erasmus program is related to the first period between 2007–2008 and 2013–2014, and Erasmus+ is the second period between 2014–2015 and 2020–2021.

student mobility is analyzed in the context of Erasmus and Erasmus+ programs over twelve years in order to: (i) compare the international mobility trajectories among European countries in terms of quantitative benchmarking (Porzio et al., 2008) by taking into account the main characteristics of the incoming and outgoing student flows over time; and (ii) identify the factors that may influence the country's performance in terms of the role they play in mobility networks, with a view to improving the assessment and quality of university services.

Starting from the European Union Open Data Portal, information is extracted and used to identify the data structures explored through a network analysis approach in line with related literature (Breznik & Skrbinjek, 2020; De Benedictis & Leoni, 2020, 2021; Derzsi et al., 2011; Kosztyán et al., 2021; Savić et al., 2017; Restaino et al., 2020; Vögtle & Windzio, 2016). To the best of our knowledge, these studies have mainly reported on outcomes without reconstructing a time perspective, focusing on the differences in countries' performances within Erasmus mobility programs over time. Moreover, in all previous studies, nothing more has been done to identify the factors that may influence a country's position and its central role in international mobility trajectories. Therefore, this study contributes to the existing literature by proposing to analyze student mobility flows through networks, not only to explore and compare the international exchange patterns but also to assess the factors determining the country's role in the transnational student mobility. For this scope, we use the Exponential Random Graph Models–ERGMs (Krivitsky, 2012; Lusher et al., 2012), one of the most important families of models used to describe the coherence of network structure.

The rest of the paper is structured as follows. After a brief overview of the state of art in international student mobility framework in Sect. 2, Sect. 3 presents the methodological perspective of the network, the network measures used to compare country performance, and the network modeling. The data collection process and some main characteristics of the Erasmus programs are described in Sect. 4, while the main results are discussed in Sect. 5. Finally, conclusions and future research agenda are reported in Sect. 6.

2 Student mobility and internationalization in higher education

Student mobility initiatives, including Erasmus programs, represent an active research area mainly to examine the roles played by countries in the internationalization process specific to higher education institutions.

As reported in Klemenčič et al. (2019), the EC has expressed high expectations for the impact of the Erasmus+ as a follow-up to the already highly successful previous program. The Commission increased the Erasmus+ budget by 40% and international mobility was among the key investments, such as joint degrees, international partnerships for innovation cooperation, and support for higher education policy reforms. Compared to the Erasmus program, participation in mobility schemes in Erasmus+ should be more clearly reflected in the quality of higher education programs and the student experience (Klemenčič & Flander, 2013).

Under Key Action 1 *Learning Mobility of Individuals* projects, participation in the Erasmus policy has increased from 3,000 participants in 1987 to 272,497 in 2013–2014, with around 954,000 individual mobility contracts concluded in 2020 under the Erasmus+ program 2014–2020 (European Commission (EC), 2021). Even if the program was impacted by the Covid-19 pandemic, its success is confirmed by the recent Erasmus+ program 2021–2027 with significant investments to achieve key features such as the inclusion of people with fewer opportunities, development of digital skills, awareness–raising on environmental issues and youth inclusion.

Given its relevance, Erasmus policy analysis has become a highly diversified field of research with different approaches (Cairns, 2019). The *macro-level* analysis quantifies incoming and outgoing mobility trends on a cross-country perspective using mainly archival data (Breznik & Skrbinjek, 2020; Choudaha, 2017; Restaino et al., 2020). These studies make a strong effort in data sources integration enriching the network data gathered from the European Open Data Portal with institutional socio-economic data from other databases (Gadar et al., 2020; Kosztyán et al., 2021). At the institutional level, research at the *meso-level* highlights exchanges among universities in specific geographical contexts. More specifically, the authors explored the phenomenon: among universities in Southern Italy (Breznik & Ragozini, 2015); to/from Slovenian higher education institutions (Breznik & Daković, 2016); among European universities measuring the level of inclusiveness of institutions welcoming students with disabilities (De Benedictis & Leoni, 2021), or the gender bias emphasizing the presence of a denser network of connections involving females (De Benedictis & Leoni, 2020) or engineering background (Breznik, 2017); among universities and companies participating in a European project (Savić et al., 2017); among Portuguese universities with a particular focus on social inclusion (Cairns & Krzaklewska, 2019). Finally, the *micro-level* studies on students assess the factors that drive the decision to study abroad (Bryła, 2019; Perez-Encinas et al., 2021), the factors shaping the network dynamics (Taha & Cox, 2016), the satisfaction with the study abroad experience (Dabasi-Halász et al., 2019) and its impact on employment and careers outcomes (Amendola & Restaino, 2017; Roy et al., 2019).

The methodological approaches in these studies have been deepened by applying a social network analysis perspective, which considers the direction of student mobility flows as weighted direct links from sending to receiving country/university. They mainly aimed at: (i) detecting the presence of attractive countries by nodal centrality and authority scores (Breznik & Skrbinjek, 2020); (ii) revealing the presence of a core-periphery structure through blockmodeling approach and clustering relational data (Breznik & Ragozini, 2015; Restaino et al., 2020); (iii) exploring the topology of the student mobility network by taking into account well-known network configurations (e.g., small world) (Derzsi et al., 2011); (iv) identifying dense groups in the giant component using community detection algorithms (Savić et al., 2017); and (iv) assessing the determinants of student mobility patterns to test for the presence of homophily effects (Vögtle & Windzio, 2016).

To the best of our knowledge, no studies to date track the main differences in both Erasmus mobility programs. Moreover, they do not research whether (and which) factors may influence the international mobility trajectories among European countries. This study, therefore, fills this gap, by adopting network centrality measures visualized in specific charts as performance tools to assess the variations in country rankings over time as well as network modeling for discovering the factors affecting student mobility at the country level.

Based on this scenario, we explore the following research questions. First, we discuss which performance indicators better describe an education system based on a country's position in the student mobility network. We then compare its performance on the basis of specific measures of network centrality, also considering the variations between the two Erasmus programs over time. We show which countries are most attractive and active in these programs, and we identify the countries that vary their performance. Finally, we explore which are the determinants that might explain country performance and its changes.

3 Methodology

In order to answer the above research questions, we used a mixed analytical strategy of analysis combining exploratory and confirmatory approaches from a network perspective. First, we identify network data structures, then we use specific network centrality indices (Freeman, 2002; Kleinberg, 1999) to compare country performance in terms of role and position in student mobility flows, and finally, we introduce the ERGM models (Krivitsky, 2012; Lusher et al., 2012) to explain the determinants affecting performances.

3.1 Network as methodological framework

Erasmus student mobility flows between countries can be modeled with an appropriate network structure. This perspective allows exploring and comparing the global structure of international relationships established over the two programs in order to identify country attractiveness criteria and to model the determinants of performances using ERGMs.

Given the set of countries $\mathcal{C}_t$ involved in the Erasmus program in academic year t, the edges $\mathcal{E}_t$ are given by the presence of students moving from one country to another. The graphs $\mathcal{G}_t$ corresponding to the networks derived for the different years contain directed and weighted links. The number of students involved in each exchange defines the edge weights ($\mathcal{W}_t$). The set of countries varies over time, given that their participation in the program is not constant.

Thus, we have twelve weighted directed graphs, $\{\mathcal{G}_t(\mathcal{C}_t, \mathcal{E}_t, \mathcal{W}_t)\}_{(t=1,\ldots,12)}$, one for each academic year, where $\mathcal{C}_t = (c_{1_t}, c_{2_t}, \ldots, c_{n_t})$ is the set of n_t countries, i.e. the set of countries at time t, $\mathcal{E}_t \subseteq \mathcal{C}_t \times \mathcal{C}_t$ is the set of edges at time t, $\mathcal{W}_t$ is the set of weights at time t, $w : \mathcal{E}_t \rightarrow \mathbb{N}_0$, and $w\left[(c_{i_t}, c_{j_t})\right] = w_{ij}^t$ is the number of students moving from a country c_{i_t} to another country c_{j_t} (with $i \neq j$) at time t. It is possible to consider the corresponding adjacency matrices $\mathbf{A}^t$ with elements $a_{ij}^t = 0$ if $(c_{i_t}, c_{j_t}) \notin \mathcal{E}_t$, and $a_{ij}^t = w_{ij}^t$ otherwise.

Given the nature of mobility flows between countries, the resulting networks are dense, well-connected, and unbalanced. Indeed, the corresponding link weights vary widely in strength, as they are strongly affected by differences in the size of countries' populations and, consequently, the number of students enrolled in tertiary education. Looking at the more recent figures available in the official statistics, the population in 2020 ranges from 38,901 in Liechtenstein to 83,170,871 in Germany, and the number of students enrolled in tertiary education range from 911 to 3,296,249 for the same countries in 2019. Such constraints require specific normalization procedures to eliminate the size effect.

In line with the normalization procedures adopted for Erasmus data (Breznik & Ragozini, 2015; Breznik & Skrbinjek, 2020), we compute the normalized adjacency matrices $\tilde{\mathbf{A}}^t = (\tilde{a}_{ij}^t)$ using:

$$\tilde{a}_{ij}^t = \frac{a_{ij}^t}{\sqrt{nstud_{i_t} \cdot nstud_{j_t}}}, \tag{1}$$

where $nstud_{i_t}$ and $nstud_{j_t}$ are the number of students enrolled in higher education programs[4] from the i-th and the j-th countries at time t, respectively. Note that this kind of normalization resembles the independence hypothesis of the χ^2 test.

[4] The data on students enrolled in higher education for all countries was gathered from the Eurostat website.

3.2 Network measures for country performance

Following the data normalization procedure described above, we derive the country's positions in the network in terms of their attractiveness for students or propensity to move abroad comparing in-degree and out-degree centrality measures (Freeman, 2002). In a directed weighted network, the number of arcs received and sent by a country defines the in-degree centrality, ${}_{in}D(c_{i_t})$, of country c_{i_t}, which represents the number of its incoming students at time t, and the out-degree centrality, ${}_{out}D(c_{i_t})$, of country c_{i_t} as the number of its out-going students at time t.

In line with related literature (Columbu et al., 2021, 2022; Santelli et.al., 2019), we considered measures of hub centrality and authority (Kleinberg, 1999) to identify the presence of good importing and/or good exporting countries, calculating two scores for each country. These measures are able to identify the most attractive and active countries in the presence of directed and weighted data, as they indicate the input or output roles played by countries in the mobility network (Doreian & Mrvar, 2021; Soldano et al., 2017) allowing the identification of countries which hold a privileged position (Restaino et al., 2020; Urbinati et al., 2021). More specifically, the hub scores are a proxy of the awareness of mobility choices taking into account the flows of students moving to a country with good authority. The authority score, in turn, is considered as a proxy for the prestige of the university, measuring the degree to which the university is able to attract students from multiple hubs. A good authority is then a country that is pointed to by many good hubs, namely *good importer*, whereas a good hub is one that points to many good authorities, in other words *good exporter*.

More formally, let us denote with

$$\begin{aligned} \overrightarrow{auth}_t &= \left(auth_{c_{1_t}}, auth_{c_{2_t}}, \ldots, auth_{c_{n_t}}\right)' \\ \overrightarrow{hub}_t &= \left(hub_{c_{1_t}}, hub_{c_{2_t}}, \ldots, hub_{c_{n_t}}\right)', \end{aligned} \tag{2}$$

the vectors of authority and hub weights of graph $\mathcal{G}_t$, i.e. authority and hub values of countries in the academic year t. In the first step, the hubs and authorities algorithm starts with the value of 1 for all hub and authority values:

$${}_{(0)}\overrightarrow{auth}_t = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \quad \text{and} \quad {}_{(0)}\overrightarrow{hub}_t = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}. \tag{3}$$

In the second step, we follow the operations:

$$\begin{aligned} {}_{(1)}\overrightarrow{auth}_t &= \mathbf{A}'^t \cdot {}_{(0)}\overrightarrow{hub}_t \\ {}_{(1)}\overrightarrow{hub}_t &= \mathbf{A}^t \cdot {}_{(0)}\overrightarrow{auth}_t, \end{aligned} \tag{4}$$

where $\mathbf{A}^t$ represents the adjacency matrix of graph in $\mathcal{G}_t$ and $\mathbf{A}'^t$ its transpose version. After k steps we get:

$$\begin{aligned} {}_{(k)}\overrightarrow{auth}_t &= \left(\mathbf{A}'^t\mathbf{A}^t\right) \cdot {}_{(k-1)}\overrightarrow{auth}_t \\ {}_{(k)}\overrightarrow{hub}_t &= \left(\mathbf{A}^t\mathbf{A}'^t\right) \cdot {}_{(k-1)}\overrightarrow{hub}_t. \end{aligned} \tag{5}$$

Following Perron Frobenius theorem (Meyer, 2000), Kleinberg's algorithm presented above, i.e., both vectors in Eq. (4), converges to the dominant eigenvectors of the crossproduct of the adjacency matrix and its transposed version. Specifically, the authority scores $auth_{i_t}$ are determined by the values of the dominant eigenvector of the authority matrix $\mathbf{A}'^t\mathbf{A}^t$, and the hub scores hub_{i_t} are given by the entries of the dominant eigenvector of the hub matrix $\mathbf{A}^t\mathbf{A}'^t$. Finally, by considering the normalized adjacency matrix, $\tilde{\mathbf{A}}^t$, the corresponding authority and hub scores, $\tilde{auth}_{i_t}$ and $\tilde{hub}_{i_t}$ can be obtained.

3.3 Network modeling

Exponential Random Graph Models (ERGMs) represent a statistical approach to modeling social networks (Lusher et al., 2012). More specifically, with ERGMs the observed network is compared to all feasible networks generated from the same number of nodes (Harris, 2013). Initially, so-called binary ERGMs modeled only the existence of edges. Later Krivitsky (2012) proposed valued ERGMs that additionally model the strength of ties.

For the sake of simplicity, let use omit the time index t and let us consider our weighted graph $\mathcal{G} = (\mathcal{C}, \mathcal{E}, \mathcal{W})$ introduced in the previous Sect. 3.1. In the ERGMs model framework, the observed graph $\mathcal{G}$ is considered a realization of a random variable $\boldsymbol{\mathcal{G}}$ with sample space $\mathbb{G} \subset \mathcal{W}^{\mathcal{E}}$, i.e., the power set of the weighted dyads in the network. Similarly to logistic regression, the aim is to model the probability of ties on the basis of some network structural characteristics. If node attributes are available (let us denote the matrix of node attributes with $\mathbf{X}$), ERGMs models allow us to include interactions between node attributes at the dyadic level.

The general form of the non-curved ERGM model for valued networks can be expressed as

$$P_{\theta,\mathbb{G},h,g}(\boldsymbol{\mathcal{G}} = \mathcal{G} \mid \mathbf{X}) = \frac{h(\mathcal{G})exp(\theta^T g(\mathcal{G};\mathbf{X}))}{\kappa_{h,g}(\theta;\mathbf{X})}, \quad \mathcal{G} \in \mathbb{G}. \tag{6}$$

In Eq. (6), θ is the q-dimensional vector of coefficients, and $g(\mathcal{G};\mathbf{X})$ represents the q-dimensional set a vector of sufficient statistics, i.e., counts of some specific configurations in the network $\mathcal{G}$, which may also depend on the node attributes $\mathbf{X}$. The coefficients and the sufficient statistics $\theta^T g(\mathcal{G};\mathbf{X}))$ define the q terms included in an ERGM model. Such terms can be classified into three levels, namely the node level, the dyad level, and the structural level. The denominator $\kappa_{h,g}(\theta;\mathbf{X})$ is defined as

$$\kappa_{h,g}(\theta;\mathbf{X}) = \sum_{\mathcal{G}\in\mathbb{G}} h(\mathcal{G})exp(\theta^T g(\mathcal{G};\mathbf{X})) \tag{7}$$

and ensures that the probability of observing network $\mathcal{G}$ is between 0 and 1.

The $h(\mathcal{G})$ term in Eq. (6) is a reference function that is an important part of the model for valued networks. The sample space $\mathbb{G}$ in the case of valued networks is often infinite or even uncountable (Krivitsky, 2012). For this reason, a restriction of the sample space by placing constraints on the w_{ij} values is required. Several reference distributions are implemented in statistical packages, such as the Binomial distribution, the Geometric distribution, the Poisson distribution, the Discrete Uniform distribution, and others (Krivitsky et al., 2023). In our study, the dependent variable is the directed tie formation via mobility of students among countries in Erasmus and Erasmus+ programs. In order to restrict the sample space, we decide to re-code the weights discretizing them into 4 values using quartiles. Therefore, for a directed link between two countries, a value of 1 was used if there is at least one student mobility from the sending to the receiving country and the number of students is less than the first quartile value of all normalized student mobilities between countries. A similar procedure is used to determine values of 2, 3 and 4. The choice of reference distribution to restrict the sample space in our model is therefore straightforward: we used the Discrete Uniform distribution for values between 1 and 4 (both values included).

By using ERGMs, we test for endogenous dependencies and exogenous attributes considering some socio-economic and cultural factors that could potentially affect the mobility flows. As for the socio-economic issue, on the node level, we estimate the effect of GDP per capita (continuous variable) for both incoming and outgoing countries. On the dyad level, the homophily effect induced by GDP per capita has been verified. In addition, region and euro currency covariates are controlled for homophily effects. As for the cultural aspect, we consider linguistic issues as the main drivers of mobility differences. Therefore, we tested the homophily effect due to belonging to the same language phylum. Even though almost all European languages belong to the Indo-European family, there are three main phyla: Romance (like Italian, French, Spanish, Romanian, etc.), Germanic (such as English, German, Dutch, etc.), and Slavic (like Polish, Czech, Slovene, etc.). The fourth category includes all other small Indo-European phyla (Hellenic, Baltic, Celtic, etc.) and other non-Indo-European languages (Uralic, Turkic, Semitic, etc.). We also tested the possible effect of having more than one official language (not just for minorities). At the node level, we tested as a country covariate, coded as a dichotomous variable. At the structural level, parameters for mutuality and triad closure were tested. The list of all terms used in our model and their description is provided below and can also be found in Fig. 1.

4 The data

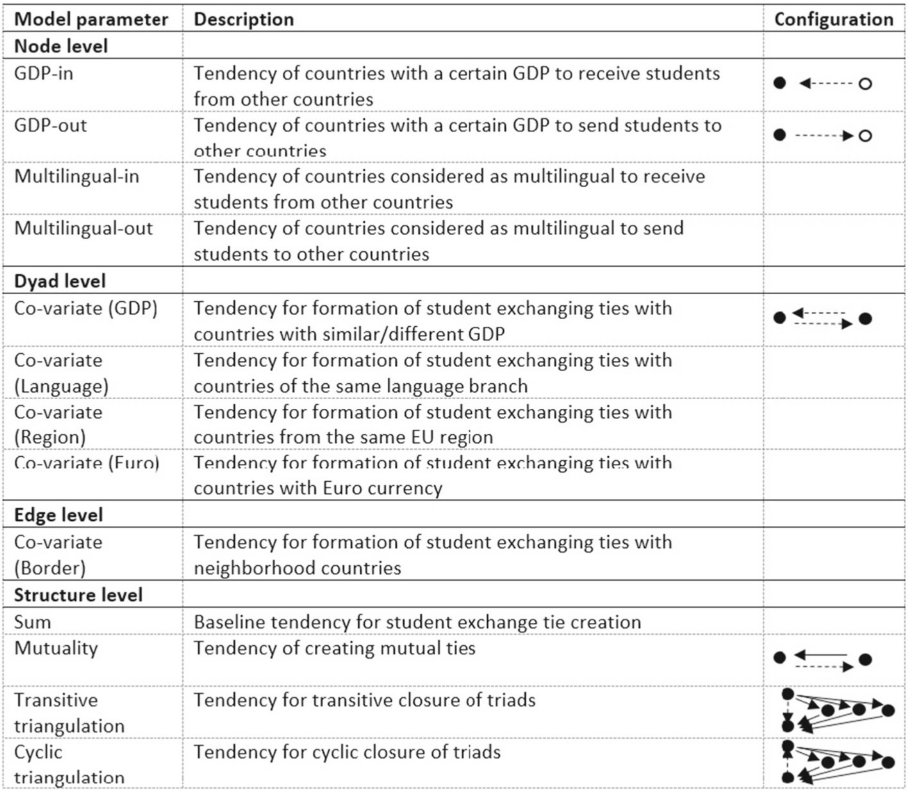
Data on international student flows among Erasmus and Erasmus+ countries have been compiled on the official EC website on Erasmus-Statistics and are freely accessible.[5] They consist of seven datasets covering the academic years from 2007–2008 to 2013–2014 for Erasmus and five datasets for the academic years from 2014–2015 to 2018–2019 for Erasmus+. The availability of official data provides stimulating opportunities for conducting a performance analysis of university quality services in promoting student mobility abroad as an internationalization policy.

As the student mobility scheme has changed from Erasmus to Erasmus+ program, the datasets have been merged to make them comparable. In the Erasmus+, student mobility is part of Key Action 1 (KA1–Learning Mobility of Individuals), in particular, KA103 is related to the mobility of students and staff in the Program Countries. The datasets for Erasmus+ contain additional observations for all mobility participants (students and staff: study exchanges and work placements for students, and teaching assignments and staff training). Therefore, after discarding the data related to traineeships and staff mobility, we obtain datasets that correspond to student mobility for studies abroad for the initial Erasmus program.

Table 1 shows the trend in student mobility for studies (SMS) and for placement (SMP) in both programs. It is particularly evident that there is an upward trend in SMS and SMP in both programs.

Before merging the datasets, a preliminary analysis is performed to integrate the information provided, since the labels differ from one dataset to another. The information under analysis includes the type of mobility (study or placement), the home and host country, the home and host university, the field of study, the gender and age of the participant, the nation-

[5] For details see https://data.europa.eu/euodp/en/data/publisher/eac.



Model parameter	Description	Configuration
Node level		
GDP-in	Tendency of countries with a certain GDP to receive students from other countries	
GDP-out	Tendency of countries with a certain GDP to send students to other countries	
Multilingual-in	Tendency of countries considered as multilingual to receive students from other countries	
Multilingual-out	Tendency of countries considered as multilingual to send students to other countries	
Dyad level		
Co-variate (GDP)	Tendency for formation of student exchanging ties with countries with similar/different GDP	
Co-variate (Language)	Tendency for formation of student exchanging ties with countries of the same language branch	
Co-variate (Region)	Tendency for formation of student exchanging ties with countries from the same EU region	
Co-variate (Euro)	Tendency for formation of student exchanging ties with countries with Euro currency	
Edge level		
Co-variate (Border)	Tendency for formation of student exchanging ties with neighborhood countries	
Structure level		
Sum	Baseline tendency for student exchange tie creation	
Mutuality	Tendency of creating mutual ties	
Transitive triangulation	Tendency for transitive closure of triads	
Cyclic triangulation	Tendency for cyclic closure of triads	

Fig. 1 Summary of parameters in the ERGMs estimation

Table 1 Distribution of student mobility in Erasmus and Erasmus+ programs

Erasmus program				Erasmus+ program			
Academic year	Total number of exchanges	Number of exchanges		Academic year	Total number of exchanges	Number of exchanges	
		SMS	SMP			SMS	SMP
2007–2008	182,697	162,694	20,003	2014–2015	299,319	221,583	77,736
2008–2009	198,523	168,193	30,330	2015–2016	300,018	215,828	84,190
2009–2010	213,266	177,705	35,561	2016–2017	325,755	236,892	88,863
2010–2011	231,408	190,495	40,913	2017–2018	340,100	244,320	95,780
2011–2012	252,827	204,744	48,083	2018–2019	351,682	248,165	103,517
2012–2013	268,143	212,522	55,621				
2013–2014	272,497	212,208	60,289				

ality of the participant, the level of study (first or second cycle), the duration of the mobility, the start and end dates, the amount of the grant received and the language used in the mobility.

Although the Erasmus program has a long history, micro-data containing the information described above are not available for all years. In particular, the age and nationality of the participant, the amount of the grant received, and the language used in the mobility are missing for some academic years and, consequently, they are discarded. In addition, although there is no information on the duration of the mobility, it is easily inferred due to the presence of the start and end dates of the mobility period. As the field of education has been previously coded with a different classification (ISCED6 1997–2011–2013), we check the correspondence between the codes and convert all codes into the more recent classification.

Some additional information for the Program Countries included in the Erasmus Student Mobility Policy has been retrieved from open data. In line with the related literature, national economic development and capacity may influence this type of mobility (Chen & Barnett, 2000; Vögtle & Windzio, 2016). Therefore, gross domestic product per capita (GDP)[6] and euro currency information was collected for all years analyzed. Given that cultural (dis)similarities are important factors of student flow (Barnett et al., 2016; Kondakci, 2011), all countries are classified into four language classes: Romance, Germanic, Slavic, and other languages. Multilingualism is tested for each country separately. Information on whether two countries share a land or sea border is also obtained. Finally, the countries are clustered regarding macro-areas into North, South, East, and West according to the United Nations publication "Standard Country or Area Codes for Statistical Use".[7]

5 Main results

5.1 Country attractiveness network performance indicators

The structure of student mobility networks among countries over time shows a slight increase in the number of countries involved and the links among them. More specifically, the number of countries has increased from 31 in 2007–2008 to 34 in 2013–2014, and the number of links goes up from 803 links in 2007–2008 to 928 links in 2013–2014. For Erasmus+, the number of countries has remained stable across the years, while the number of links increases steadily over the entire period (Table 2).

In addition, the Erasmus mobility networks have changed, especially in terms of the number of students involved in both programs, which represents the weight of the links between country pairs. Overall, the number of students who joined the Erasmus and Erasmus+ programs has increased. In the first period, the increase is almost constant across the years, while in the second period, the highest peak is observed between 2014–2015 and 2015–2016.

Figure 2 shows the distribution of Erasmus and Erasmus+ students by country over the twelve academic years. Spain, France, Germany, and Italy are very attractive, being the top destinations for both incoming and outgoing students. Spain in particular has the highest number of students in terms of both incoming and outgoing exchanges. France and Germany rank second and third for incoming students, while the situation reverses for outgoing students. Italy is in fourth place for both incoming and outgoing students.

In addition, Fig. 2 reports the ratio of incoming to outgoing students in line with the coverage ratio used in trade networks to analyze the trade balance of foreign countries.

[6] The data on GDP was downloaded from the World Bank website.

[7] The document is available at https://unstats.un.org/unsd/methodology/m49/.

Table 2 Number of countries involved in the Erasmus student mobility for studies, from 2007–2008 to 2019–2020

Academic year Erasmus program	Country	Number links	Number students	Academic year Erasmus+ program	Country	Number links	Number students
2007–2008	31	803	162,694	2014–2015	33	865	145,717
2008–2009	31	807	168,193	2015–2016	33	899	217,153
2009–2010	32	823	177,705	2016–2017	33	911	221,488
2010–2011	33	839	190,495	2017–2018	33	911	226,646
2011–2012	33	919	204,744	2018–2019	33	932	231,277
2012–2013	33	910	211,995				
2013–2014	34	928	212,208				

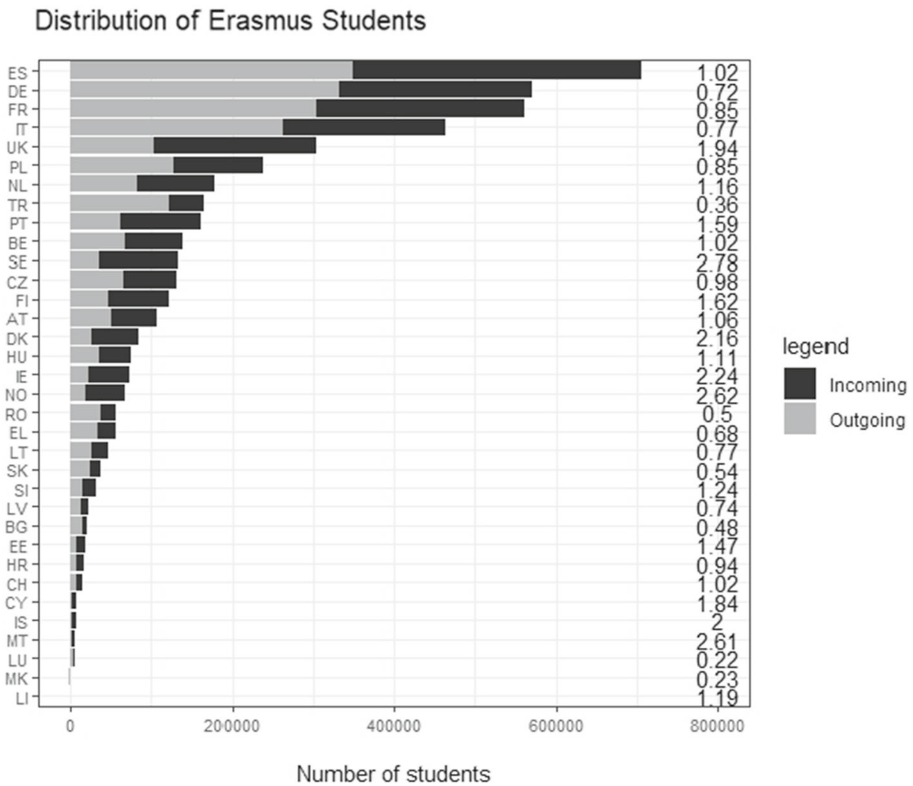


Fig. 2 The distribution of Erasmus and Erasmus+ students (incoming and outgoing) for all countries. The ratio between incoming and outgoing students is shown at the end of each bar

Values greater than one indicate the attractiveness of countries with more incoming compared to outgoing students. The Scandinavian countries (Sweden, Norway, and Denmark) present the highest ratio values, while the United Kingdom appears to be the most attractive. Spain, France, Germany, and Italy seem to be slightly more export-oriented.

Given the normalized adjacency matrix from Eq. (1), $\tilde{\mathbf{A}}^t$, and the corresponding authority and hub scores, $\tilde{auth}_{i_t}$ and $\tilde{hub}_{i_t}$, we compare the performance of countries in two representative years of the two programs using a Dumbbell Chart that is able to highlight the absolute values of the scores and their variations over the time. We have chosen 2010–11 and 2016–2017 as reference years because they can provide more stable information as they are in the middle of the period analyzed.

The highest authority scores in 2010 are reported by the five largest European countries (Spain, France, Germany, United Kingdom, and Italy) (Fig. 3). In particular, Spain, France, Germany, and Italy also have a hub position which reveals their role both in attracting and sending students. These countries play a prominent role in all years of the first program. In the Erasmus+, Finland and Greece have gained a central position for both authority and hub scores, while France and Spain lost their leading roles. The position of Italy and Germany, as well as the UK, Poland, Portugal, and the Netherlands, has remained almost unchanged, as they are actively attracting many incoming students from other countries.

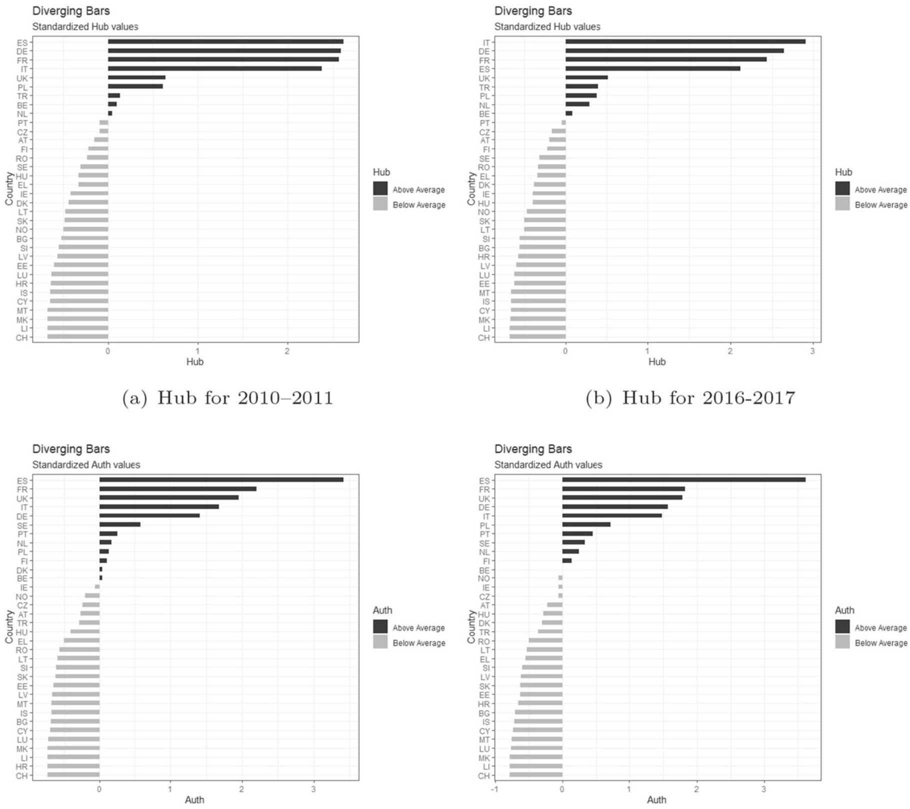
These changes are confirmed by Dumbbell Charts (Fig. 4) showing, for each country, the variations between the authority and hub scores averaged over the first (black dots) and the second (grey dots) program. Spain and France have the largest negative variations, while Finland and Greece report the largest positive variations. Poland, the Czech Republic, and Croatia also have large positive values with a central position in the network.

All these first exploratory results confirm that the new Erasmus+ rules and some socio-political changes over the last ten years have modified the global structure of student network mobility patterns.

5.2 Determinants of network mobility flows

Table 3 provides the results of the ERGMs model estimation for the two academic years 2010–2011 and 2016–2017. The tested effects are explained in Fig. 1. Starting with the node-level effects, we observe positive and significant effects of GDP per capita on receiving students in both models. The coefficient 0.573 in 2010–2011 indicates that countries with higher GDP received approximately 77% ($e^{0.573} - 1 \doteq 0.77$) more students than expected by chance. In 2016–2017, this percentage increased to 103% ($e^{0.708} - 1 \doteq 1.03$). The negative and significant effect of GDP per capita in the first model indicates that countries with higher GDP per capita were less active in sending students. More specifically, 39% ($e^{-0.492} - 1 \doteq -0.39$) fewer students than expected were sent from countries with higher GDP in 2010–2011. This effect was no longer significant in 2016–2017. Multilingual countries received and sent significantly fewer students in both periods. In 2010–2011 approximately 44% ($e^{-0.584} - 1 \doteq -0.44$), and in 2016–2017 approximately 33% ($e^{-0.402} - 1 \doteq -0.33$) less students than expected were received in multilingual countries. A 41% decrease in 2010–2011 and a 33% decrease in 2016–2017 in outgoing students from multilingual countries are observed.

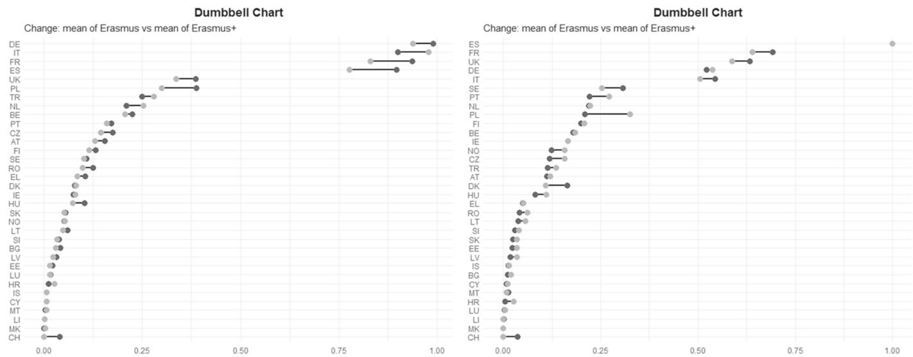
At the dyad level, the strong negative and significant effect of the absolute difference between GDP per capita indicates a strong homophily effect, meaning that countries with similar GDP per capita are more likely to share students. A strong and positive significant homophily effect is identified among countries from the Romance language phylum, while a significant negative effect is identified among countries from the Germanic language phylum. On the one hand, the number of exchanges among Romance language phylum countries is almost three times higher than expected ($e^{1.363} - 1 \doteq 2.91$ in 2010–2011, and $e^{1.357} - 1 \doteq 2.88$ in 2016–2017). On the other hand, the number of exchanges among Germanic language



(a) Hub for 2010–2011 (b) Hub for 2016-2017

(c) Auth for 2010–2011 (d) Auth for 2016-2017

Fig. 3 Diverging bar plot of countries according to hub and authority standardized scores. Bar color: black above average; grey below average



(a) Hub (b) Authority

Fig. 4 Dumbell Charts visualization of the difference between mean hub and authority scores in Erasmus (black dots) and Erasmus+ (grey dots) programs per each country

Table 3 Results of ERGMs estimations

	2010–2011			2016–2017		
Node level						
GDP-in	0.573	(0.101)	***	0.708	(0.079)	***
GDP-out	− 0.492	(0.087)	***	− 0.079	(0.081)	
Multilingual-in	− 0.584	(0.103)	***	− 0.402	(0.095)	***
Multilingual-out	− 0.528	(0.098)	***	− 0.401	(0.104)	***
Dyad level						
Covariate.GDP	− 1.592	(0.120)	***	− 1.819	(0.120)	***
Covariate.Germanic	− 0.567	(0.123)	***	− 0.809	(0.140)	***
Covariate.Slavic	− 0.377	(0.177)	*	0.198	(0.153)	
Covariate.Romance	1.363	(0.261)	***	1.357	(0.238)	***
Covariate.Other	0.325	(0.281)		− 0.339	(0.248)	
Covariate.North	− 0.012	(0.168)		− 0.455	(0.174)	**
Covariate.South	− 1.283	(0.188)	***	− 1.232	(0.158)	***
Covariate.East	− 0.539	(0.183)	**	− 0.316	(0.151)	*
Covariate.West	0.352	(0.173)	*	0.305	(0.232)	
Covariate.Euro	− 0.287	(0.079)	***	0.101	(0.073)	
Edge level						
Covariate.Border	0.008	(0.132)		0.250	(0.125)	*
Structure level						
Sum	− 0.981	(− 1.023)		− 5.617	(0.983)	***
Mutuality	− 0.121	(0.147)		0.514	(0.139)	***
Transitive triangulation	1.463	(0.269)	***	0.539	(0.246)	*
Cyclic triangulation	− 0.116	(0.085)		− 0.173	(0.131)	
AIC	− 950.888			− 933.385		
BIC	− 856.606			− 839.103		
Log Likelihood	494.444			485.693		

***p $<$ 0.001; **p $<$ 0.01; *p $<$ 0.05

phylum countries is approximately 43 and 55% lower than expected in 2010–2011 and 2016–2017, respectively.

Regarding geographical macro—areas, for both models, strong negative and significant effects are found in the South and less strong but still negative and significant effects in the East. More specifically, countries in Southern Europe exchanged 73% fewer students than expected in 2010–2011 and 71% fewer students than expected in 2016–2017. Regarding exchanges among the Eastern countries, the decrease varied between 42% in 2010–2011 and 27% in 2016–2017. In the North, a negative and significant effect of approximately 37% ($e^{-0.455} - 1 \doteq -0.37$) less student mobilities than expected is observed in 2016–2017. In the West, the only positive and significant effect identified in 2010–2011 is related to regional homophily, with approximately 42% ($e^{0.352} - 1 \doteq 0.42$) more student mobility than expected. A positive and significant effect of approximately 28% ($e^{0.250} - 1 \doteq 0.28$) more student mobilities than expected in relation to the common border is identified in the second model (for 2016–2017) but is not significant in the first model (for 2010–2011).

In the ERGMs structure-level effects, the first term is the edge effect, which is equivalent to the intercept in the regression model. Non-significant result of mutuality in the first period suggests that the sharing of students between countries in the first period is not reciprocal. However, this coefficient is positive and significant in the second period indicating approximately 67% ($e^{0.514} - 1 \doteq 0.67$) more correlations among countries than expected. Regarding the configuration of the triads, there is an indication of a tendency towards a hierarchical circuit exchange in both periods. In 2010–2011, over three times more transitive triads than expected ($e^{1.463} - 1 \doteq 3.32$) are found. This term drops to 71% ($e^{0.539} - 1 \doteq 0.71$) in 2016–2017.

6 Conclusions

Erasmus is one of Europe's biggest investments in higher education systems to promote the international mobility of both students and staff. Countries play different roles in this process and adopt different strategies to lead the way in terms of attractiveness for incoming as well as outgoing student flows.

Previous contributions to international student mobility focused primarily on the period between 2007–2008 and 2013–2014. The present study compares the results of the two Erasmus programs in terms of performance analysis. By using network centrality measures, it has been possible to compare the performance of countries, contributing to the understanding of the challenges of student mobility in Europe. The main findings confirmed the leading role of four countries, Spain, Italy, France, and Germany, which have a central position in the student mobility networks (Breznik & Skrbinjek, 2020). However, these results also offer new insights into Erasmus mobility agenda and raise new questions and issues. More specifically, these four countries with high authority scores have had a stable position over time. Italy has even strengthened its position, while the other three leading countries have lost some momentum. When comparing the two programs, the ranking of countries in terms of outgoing students is very similar. In terms of attractiveness for incoming students, the UK has joined the group of four countries. However, in Erasmus+, the UK, together with France, lost the most popularity compared to the first program, making Spain even more dominant as the most attractive country. Due to its socio-economic situation, Poland has gained the most over the last decade, followed by Portugal.

The network modeling results provided some clues for understanding which are the determinants affecting the countries' performance. Model parameters seem to be very stable, and both socio-economic and cultural issues have affected student mobility flows among countries. A homophily effect of GDP per capita and Romance language is confirmed in both programs. Developed countries with higher GDP are recognized as even slightly more attractive in the Erasmus+ program. The effect of homophily for regions within Europe is not confirmed, suggesting that students are aiming at countries from other regions. Slightly surprising to this context, common border is becoming an issue. Although using the same language has proved to be a very important cultural homophily effect (Vögtle & Windzio, 2016), it has only been partially confirmed. We have in fact tested each language branch separately and a relevant stable homophily effect is confirmed for the Romance language branch. For Slavic and Germanic language branches, even negative homophily effects are present. Multilinguality has been shown to have a more negative effect. Finally, the Euro currency never seems to restrict the mobility choices of students.

Our analysis yields some important findings on the macro-level. In general, the Erasmus mobility process initiated by the European Commission seems to be very stable. There had been some concerns in the past, in particular regarding the expansion of Erasmus and the integration of different actions (Kondakci et al., 2018). However, the transition seems to be smooth and delivers that results, while expected by the EC, are no less desirable.

As practical implications of our analysis, although the data refer to the country level, policy makers of universities can consider these results in their decisions to improve institutional internationalization. They can increase the number of agreements by selecting partners from attractive countries. In that way, institutions should introduce policies in order to improve the quality of services by taking into account the specific characteristics of both Erasmus programs. Furthermore, students could acquire useful information in terms of choosing a mobility destination in line with their individual needs and future job perspectives.

As further research guidelines for future work, firstly, our study only monitors mobility abroad between Program Countries and neglects these student exchanges to Partner countries. Secondly, the network approach based on country-level data could be extended to the university level in line with other related contributions (Derzsi et al., 2011; De Benedictis & Leoni, 2020, 2021), also considering a multilevel model approach for mobility data (Santelli et. al., 2022). Furthermore, more institutional characteristics could be gathered to reveal insights. Finally, the application of specific statistical models for longitudinal network data, i.e. network dynamic models (Snijders, 2017), could be adopted to capture the richness of student mobility patterns over time, especially for the second phase of the Erasmus program.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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