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# From strugglers to superstars
## Assessing the roles of European regions in knowledge flows

Cardoso, Rodrigo Viseu; Uyttebrouck, Constance; Dąbrowski, Marcin

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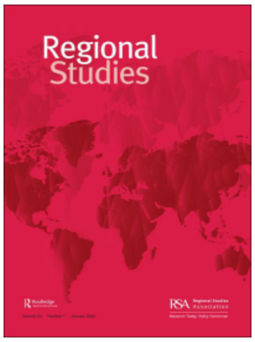


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# From strugglers to superstars: assessing the roles of European regions in knowledge flows

Rodrigo Viseu Cardoso[a], Constance Uyttebrouck[b] and Marcin Dąbrowski[a]

**ABSTRACT**
This paper develops a typology of European regions according to their role in knowledge exchange networks. Knowledge flows are critical economic assets, but it is essential to qualify as well as to quantify them to understand how they reflect regional inequalities and regional roles in networks. Using Horizon 2020 partnership data, we perform a cluster analysis of European NUTS-2 regions using multiple flow indicators and derive five types of engagement in knowledge flows. We then explore the resulting regional 'flow profiles' and clarify the drivers and barriers to becoming a high-performing knowledge region, providing valuable insights for regional policymakers and planners.

**KEYWORDS**
regional innovation systems; interregional knowledge flows; innovation policy; Horizon 2020

**JEL** R1
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## 1. INTRODUCTION

Regions are engines of economic growth and innovation relying on effects of agglomeration and proximity, which help create strong networks of economic and knowledge actors. These features make regions the spatial focus of industrial and innovation policies, advocated by various international organisations. The growing importance of the regional tier of government is also reflected in a long-term trend towards political decentralisation from central to regional authorities in most developed countries. The changing role of regions and policies to stimulate their economic development and innovation capacity has been reported extensively in this journal (Capello & Lenzi, 2015; Huggins et al., 2018; Pugh, 2017).

The diversity of regional contexts and the uneven distribution of assets that help regional economies thrive result in a highly imbalanced regional development, from globally connected regions with strong industrial clusters and innovation potential, to declining old-industrial regions locked in outdated branches or peripheral regions with scarce economic activity. Regional economic disparities have negative impacts, in terms of not only economic and social decline, but also disillusionment with democracy (Dijkstra et al., 2020; Rodríguez-Pose, 2018). This requires attention from policymakers to develop place-specific innovation capacities in lagging regions (Lagendijk & Lorentzen, 2007; Morisson & Doussineau, 2019).

Knowledge networks are no exception to these disparities. Although the context of growing competitiveness to develop a knowledge economy makes interregional knowledge flows key regional assets for growth and innovation, knowledge is unevenly and selectively distributed across regions. On one hand, the likelihood that different regions exchange knowledge collaboratively depends on various types of proximity, including social or organisational (i.e., the role of individuals or institutions) and geographical (Autant-Bernard et al., 2007; Lagendijk & Lorentzen, 2007). On the other hand, regional characteristics influence the distribution of knowledge flows, based on the compatibility and diversity of industrial and technological profiles (Bettarelli & Resmini, 2022; Capone et al., 2021), the attractive capacity of leading cities (Bianchi et al., 2023; Verginer & Riccaboni, 2021), and various internal economic, technological and infrastructural conditions (Wanzenböck et al., 2013).

Designing regional innovation policies therefore requires understanding how regions exchange knowledge. More specifically, it is important to know whether regions can access knowledge-sharing networks, what role they play, and what that tells us about the interregional

**CONTACT** Rodrigo Viseu Cardoso r.o.v.cardoso@tudelft.nl
[a] Department of Urbanism, Delft University of Technology, Delft, the Netherlands
[b] Urban Development and Mobility Department, Luxembourg Institute of Socio-Economic Research (LISER), Esch-sur-Alzette, Luxembourg

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circulation of knowledge. In fact, gaps in innovation capacity between regions can be bridged by improving the interregional redistribution of knowledge flows, for example, through shared institutional environments (Bergman & Maier, 2009), or geographical, functional and sectoral proximity (Maggioni & Uberti, 2009). This becomes more important as interregional flows – including knowledge – face increasing geopolitical barriers to global connectedness. The European Union (EU) aims to become less vulnerable to global disruptions by reorienting its economy inwards (Capello et al., 2024). It is therefore critical to map how different regions engage in interregional flows at the European scale to help them make the most of their network roles.

Despite the growing literature on the use of knowledge and the role of networks in fostering innovation within regions (De Noni et al., 2018; Navarro et al., 2009; Tödtling & Trippl, 2005), there are fewer insights on how knowledge circulates between regions. Therefore, this paper aims not only to quantify but also characterise the circulation of interregional knowledge flows in Europe. It does so by developing a multi-indicator framework broadly inspired by pair-level metrics in network analysis that allows the differentiation of various features of knowledge flows beyond their size. This allows us to carry out a cluster analysis to extract a typology of regions based on a novel definition of the 'flow profile' determined by these combined features.

The approach addresses an important knowledge gap, as research has often emphasised flow intensity to measure regional performance under the assumption that 'more' is better, overlooking other relevant features of flows. In some regions it may be more important to be connected with many different regions than to have intensive exchanges with a smaller number of partners; other regions may experience imbalances at the national level (e.g., monocentric versus polycentric systems) regardless of their flow intensity; others may be too specialised on a specific flow type or direction, or too dependent on relations with preferred regions, becoming vulnerable to shocks in those regions; finally, some regions may consistently coordinate large knowledge networks, while others can only expect to be participants in existing partnerships. These aspects help characterise knowledge networks and network roles and evaluate regional capacities and resources. Therefore, we add nuance to existing discussions by developing a multidimensional characterisation that combines various specificities of interregional flows. A typology differentiating regions on the basis of the features of their flows, rather than economic or geographical characteristics of the respective nodes, allows finding regional similarities and differences that would otherwise remain unnoticed. It also helps us understand to what extent regional features are associated with specific knowledge flow types, and whether these types denote an uneven distribution of access to, or participation in, knowledge networks.

Earlier literature has usually focused on small sets of cases to extract detailed information (Maggioni & Uberti, 2007, 2009; Makkonen & Inkinen, 2013; with exceptions, see Wanzenböck et al., 2013) and a comprehensive overview of regions is missing. Moreover, many previous datasets miss recent developments affecting knowledge flows. Therefore, we use a recent dataset that covers 329 NUTS-2 regions in 32 countries at two points in time (2015 and 2020). We focus on the formation of Horizon 2020 (H2020) consortia, the EU Framework Programme for Research and Innovation, the largest innovation instrument ever. Open to knowledge institutes and governmental, market and non-governmental actors, H2020 is a comprehensive illustration of how institutions carry and exchange knowledge, providing standardised datasets that allow a consistent measurement of flows across European regions. Similar datasets of EU-led research and development (R&D) collaboration have been used in previous research (Autant-Bernard et al., 2007; Balland, 2012), although these examples deepen their analysis of what influences network formation by using a sample of projects in specific sectors. Since our aim is to construct a typology of knowledge flows across regions and sectors, we adopt a comprehensive view of all the H2020-funded research projects in the study period.

A key challenge of this analysis lies in translating complex, multi-participant project structures into a coherent framework that measures various flow features between any two regions, as mentioned above. H2020 projects often involve multiple partner regions with distinct roles, namely coordinators and participants. This creates methodological difficulties when translating their flows into a paired matrix, which fails to capture the hierarchical and networked nature of these partnerships. Notably, distinguishing between coordinator and participant roles, especially when they persist over time, provides key insights into regional power relations and hierarchies. However, representing that distinction requires focusing on the flows between regions taking these roles, rather than all partner-to-partner flows. Without this step, the asymmetries that we want to detect would be overshadowed by the large volume of regular participant flows, masking critical patterns of dominance, partnership access and knowledge leadership. While this approach limits the ability to fully capture interactions between all partners, it moves the study beyond conventional network analysis by focusing on the directional dynamic and hierarchical structure of knowledge flows. We discuss specific steps aimed at clarifying this approach in the methodology section and revisit its limitations in the conclusions. The next section develops the conceptual framework of the multi-dimensional flow analysis and argues for the power of a metric that goes beyond intensity as the only measure (and policy aim) of flows. Then, we elaborate on the methodology of data retrieval and aggregation and generation of the regional typology before presenting the cluster analysis results. We characterise each cluster and pinpoint the critical changes between the 2015 and 2020 datasets both in the cluster grouping and cluster changes. Then we briefly discuss the various clusters from the perspective of access to, and participation in, knowledge networks, searching for additional factors that may explain why some stand-out features contribute to generating unique types, and commenting on a few outliers. The conclusions establish the findings and limitations and provide directions for further research.

## 2. THEORETICAL BACKGROUND

### 2.1. The mutual dependence between knowledge flows and regional development

Interregional networks enhance regional innovation by providing knowledge resources that can be integrated into the local economy. Such processes rely on factors such as the density, complementarity and geographical characteristics of networks (Ascani et al., 2020) and regional features, such as population, size or density as well as transactions, networking and spillovers related to patents, spin-offs or the mobility of highly skilled workers (Trippl & Maier, 2011). Network nodes include universities, research institutes and firms, which are particularly important for peripheral regions' innovation and growth (Bergman & Maier, 2009). In such regional contexts, which tend to remain on the margin of new economic trends and innovation, plugging into external knowledge networks beyond regional boundaries can be a promising strategy to overcome peripherality, as opposed to strategic striving to build local 'buzz' through intra-regional interactions (Rodríguez-Pose & Fitjar, 2013). Developing interregional networks positively influences the capacity of peripheral regions to diversify their economies (Balland & Boschma, 2021) and sourcing exogenous knowledge can compensate for the 'thinness' of their innovation systems (Trippl et al., 2018).

Regional characteristics influence network formation at several scales. Regions with similar profiles (e.g., regarding technology or industrial development) are more likely involved in large networks (Bettarelli & Resmini, 2022). A region's central position within knowledge networks relies on its internal capacity, economic conditions, technology infrastructure and spatial spillover impacts (Wanzenböck et al., 2013). Regions where the local knowledge base builds on both local and non-local network ties perform better in knowledge production (Van der Wouden & Rigby, 2019). At the urban scale, cities that are more globalised and/or centrally positioned in networks have a higher patenting activity (Bianchi et al., 2023) and more capacity to retain the most prolific scientists (Verginer & Riccaboni, 2021).

Irrespective of the scale of analysis, proximity is determinant for knowledge flows and collaboration within networks. Boschma (2005) defines five proximity types: geographical (face-to-face interactions), cognitive (similar knowledge bases), organisational (proximity between companies, depending on the degree of autonomy and control induced by their link), institutional (similar formal and informal rules and constraints between actors) and social (common relationships through factors such as trust). Organisations that share at least one of these forms of proximity are more likely to cooperate. In particular, social proximity (e.g., through a network or community) improves trust and enhances reciprocation (Agrawal et al., 2008). Still, geography is the most obvious dimension determining interregional knowledge flows (Maggioni & Uberti, 2009). It benefits individuals who are not socially or professionally close, namely to access tacit knowledge (Gui et al., 2018) and favours network centrality given the spill-over effect of leading regions, except in the case of clusters of super-central regions (Maggioni & Uberti, 2009). Increased distance lowers the effects of variety and the benefits of spillovers (Eriksson, 2011). Studies on EU-funded R&D consortia found that geographical, organisational, and institutional proximity are likely to facilitate collaborations, while cognitive and social proximity play a less significant role (Balland, 2012). That said, others found that social distance may have more influence than geographical distance for regional cooperation on research (Autant-Bernard et al., 2007) as it enriches local knowledge bases (Breschi & Lenzi, 2016).

Conversely, the structure of knowledge networks influences regional innovation capacity and productivity in different ways (Capone et al., 2021). For example, densely connected networks hierarchically structured in subnetworks are beneficial to urban innovation, especially in cities where firms need to access cognitively distant knowledge bases. Other beneficial factors of productive knowledge exchange include open and dense collaboration networks, the involvement of actors from knowledge-intensive regions, and interconnectivity between such regions (De Noni et al., 2018). Multi-scalar networks, in which global scale inputs enter the regional economy in a directed way through the gatekeeping role of local firms, also increase regional innovation (Ascani et al., 2020).

### 2.2. Knowledge flows and innovation: moving away from intensity

Often, studies about the drivers of knowledge flows focus on how they impact *flow intensity*, or the *amount* of knowledge transferred to or from a region, eventually weighted for population. For instance, both Ascani et al. (2020) and Capone et al. (2021) use patents or innovations per capita as the dependent variable of the effects of various network features. Autant-Bernard et al. (2007), also using EU-funded research projects, build different models based on number of projects and number of partners. There is however a case to diversify this focus on intensity and characterise knowledge flows according to other features that matter for regions. We present five additional features that influence regional innovation and help us build a multi-indicator metric of analysis.

Knowledge flows rely on the social embeddedness of actors in informal and formal systems (Phelps et al., 2012) and higher institutional quality helps regional actors join networks at various scales (Hassink & Marques, 2016). While regions lacking efficient institutions rely more on networks and foreign investment from knowledge-intensive regions (De Noni et al., 2018), *interregional imbalances* exist even in countries with high overall institutional quality (Lipps & Schraff, 2020). For instance, dominant capital city-regions historically benefitted from self-reinforcing cycles of policy and investment (Hohenberg, 2004) to capture most flows, while peripheral regions needed to connect with external knowledge actors to compensate for their disadvantages (Tödtling & Trippl, 2005). These cases suggest that, while network intensity might be constrained, *network connectivity*, the ability to connect with many partners in many fields, can increase innovation diffusion and performance. Indeed, linking many firms and institutions through different kinds of partnerships in specific fields creates strategic resources for innovation and regional economic attractiveness (Krätke & Brandt, 2009).

The innovative capacity generated by these partnerships can be improved through the variety and intensity of local knowledge and external knowledge transfers (Tavassoli & Carbonara, 2014). However, less competitive or peripheral regions may lack the knowledge infrastructure to accommodate this variety, making regions dependent on fewer actors that also underperform compared with others in more competitive regions (Huggins & Johnston, 2009). This implies a selectivity in knowledge exchanges, as such regions can only rely on few partner regions and knowledge areas, thus becoming vulnerable to unexpected shocks or policy changes in those regions. To overcome this *network selectivity*, these regions need effective institutions (Rodríguez-Pose & Di Cataldo, 2015) and organisational, cognitive and technological proximity with core regions to compensate for their remoteness and organisational thinness (Eder, 2019). But, conversely, core regions gain a strong influence on flows to and from smaller and peripheral regions. To avoid excessive *external influence* of these dominant players, more diverse connections must be made to global knowledge, for example, through innovative universities and firms consistent with local needs (Pinto et al., 2015).

One tool of regional innovation are learning clusters (Hassink, 2005). They allow learning in intra- and interregional knowledge flows, producing knowledge internally, and benefit from systemic resources from external networks (Expósito-Langa et al., 2015). Firm clusters and knowledge providers have to develop and source knowledge internally and externally, either from explicit policy (Coenen & Asheim, 2012) or organically (Doloreux & Dionne, 2008). Such relations develop in regional innovation systems (RIS), systems of interconnected organisations building upon territorial features that matter for innovation and learning (Pino & Ortega, 2018). RIS connect knowledge-producing organisations and clusters of companies, and this capacity drives innovation as long as they take part in an 'innovative milieu' (Camagni, 1995) powered by external networks through which knowledge circulates. In this context, evaluating the local *balance between incoming and outgoing knowledge flows* is needed to determine the regional role in a knowledge network. An RIS must be able to generate 'local buzz' while being connected to global pipelines of knowledge (Bathelt et al., 2004).

## 3. RESEARCH DESIGN

### 3.1. Building a multidimensional characterisation of flow profiles

As section 2 shows, knowledge flows matter for regions in various ways beyond their intensity. The number of connections with other regions, the distribution of flows within a country, the reliance on a variety of partners and fields, the influence exerted on other regions, and whether regions play a stronger role as producers or receivers of knowledge, all determine the characterisation of flows and can be exploited by a region. Therefore, our multi-dimensional analysis articulates various aspects of knowledge flows into an encompassing 'flow profile', allowing a better understanding of interregional networks and eventually more appropriate policy recommendations. Our conceptual approach is summarised in Figure 1, followed by an explanation of the indicators we use.

- *Intensity* is the simplest measure of the strength of each region as a sender or receiver of knowledge, measured in the units that matter for the analytic framework. Although it overemphasises regions leading larger networks, the indicator reflects the level of dominance of these regions and establishes regional hierarchies.
- *Weighted Intensity* looks at intensity in relation to the total regional population, a standardising measure which allows broader comparability. This corrects the bias of the previous indicator and allows the assessment of regions according to their own relative capacity.
- *Connectivity* measures the number of nodes each region is connected with. Regardless of the intensity of the connections, this indicator differentiates between regions which are focused on a small set of partners, and those which have many spatially dispersed connections.
- *Interregional Balance* assesses the level of dominance or decentralisation of a region within its country. Some regions capture a vast majority of the national flows, while other countries exhibit a balanced regional system. This is relevant as there are policy arguments on the desirability to distribute capacity throughout regions or invest more in a national core region.
- *Send–Receive Balance* considers the direction of flows, testing whether regions are 'senders' or 'receivers' of knowledge, conceptualised here as roles of leadership or mere participation in networks. This is relevant because, considering that there are different implications in consistently playing these roles, policy priorities can be considered for different situations.
- *Network Selectivity* measures how much a 'sender' region relies on a single preferred partner as 'receiver', and, conversely, a 'receiver' region relies on a single sending partner. This matters because unexpected events or policy changes in the destination may affect the outgoing flows of a region if it has a large focus on that destination, and vice versa.

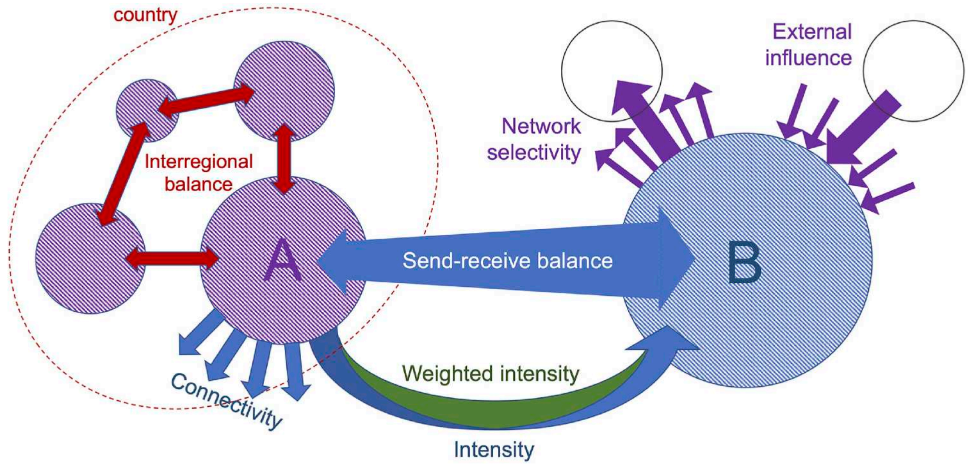



**Figure 1.** Conceptual diagram of regions A and B related by seven flow indicators: Connectivity, Intensity, Weighted Intensity, Interregional Balance, Network Selectivity, External Influence and Send–Receive Balance.
Source: Elaboration by authors.

- *External Influence* is related to network selectivity. From the sender perspective, it asks how much the knowledge flows generated in that region of origin contribute to the incoming flows of the main partner destination. From the receiver side, it asks how much the flows coming from a preferred sending partner contribute to the total number of outward flows of that partner.

## 3.2. Aggregation of flows at the NUTS-2 level and matrix compilation

Our analysis is based on the project European Spatial Planning Observation Network (ESPON) IRiE – Interregional Relations in Europe. IRiE aimed to generate new data and evidence about interregional relations in Europe, and analysed flows of goods, services, people, capital and knowledge between all NUTS-2 regions in the ESPON space (EU-27, UK, Iceland, Norway, Liechtenstein and Switzerland).[1] The paper focuses on H2020 networks and compiles all research partnerships established between organisations located in 329 NUTS-2 regions in 32 countries between 2015 and 2020. The compilation is based on the CORDIS database, which lists all H2020 projects, their coordinating partner and the participants involved. It should be specified that the focus on H2020 is necessarily oriented towards larger publicly funded institutions and does not cover other dimensions of knowledge flows resulting from, for example, product innovation.

We excluded projects carried out by single partners (lacking interregional flows) or including third-country partners (lacking NUTS-2 information) to extract 10,778 projects. Since CORDIS data are not geocoded, the list of partner organisations (place names and postcodes) was then associated with Eurostat LAU-2 name lists. Manual searches were performed for missing place names, mainly due to inconsistent spellings across datasets. This was aggregated regionally, obtaining 39,293 organisations with NUTS-2 data. In the project list, all participant names were replaced by their respective NUTS-2 code, keeping the structure of rows for individual projects and columns for participant regions (where the first column corresponds to the coordinator).

To turn this list into an input-output matrix, some methodological decisions were needed. Most flows can be modelled as exchanges between pairs of regions, with senders and receivers corresponding to rows and columns – students moving from A to B, remittances from B to A, etc. H2020 partnerships, however, are networks varying from two to 38 participants,[2] which does not translate into a paired origin-destination matrix. To overcome this issue, each project coordinator was classified as a 'sender' (or 'origin'), each project participant as a 'receiver' (or 'destination'), and each coordinator-participant pair counted as one matrix instance, regardless of how many such pairs belong to the same project. For instance, in a project with ten partners, counting coordinator-participant pairs means that coordinating region A adds nine instances to its total as 'sender' (row). But each participating region B only adds one instance to its total as 'receiver' (column), namely its link to the coordinator. Region A has one *project* but several *coordinating roles*; that is, the values in the matrix do not correspond to the number of projects held by the region but to the number of partnership pairs. This is why the results of the 'send' rows and 'receive' columns add up to the same, which is mandatory for the matrix to work.

This option neglects regular partner-to-partner connections and favours coordinating regions, whose results are inflated in relation to the partners. Another option to make the matrices mathematically consistent would be to count every pair of regions in a consortium as one instance (a group of $n = 10$ partners would have $n(n - 1)/2 = 45$ instances). However, besides leading to several million send–receive pairs, increasing the risk of errors when performing the necessary manual checks for missing partner names and inconsistent spelling, the approach would erase the distinction between coordinator and participant roles, turning the Send–Receive Balance indicator

**Table 1.** Horizon 2020 projects, mean partnership size and variation, 2015 and 2020.

| Year | Mean no. partners | SD | Interquartile range (IQR) |
|---|---|---|---|
| 2015 | 6.30 | 3.97 | 5 (3–8) |
| 2020 | 6.92 | 4.09 | 5 (4–9) |

irrelevant and affecting what can be said about hierarchies and dominance in research networks. While the bias is sometimes significant, entirely removing it and equalising all roles would not adequately represent the potential gains for a region able to lead many projects, rather than just join existing ones. The approach thus supports the fact that knowledge flows both ways between coordinators and partners, but also the assumption that coordinating regions gain more from research projects than partners. We acknowledge this limitation and, although the bias can be excessive in the case of very large consortia, these are exceptions. Table 1 helps quantify the implications of the method, showing the mean partnership sizes around a moderately compact range of values.

Finally, an R script places the coordinating partner region cell in a matrix row (sender), counts its partnership pairs and the number of occurrences of regions appearing as receivers, and places the counts in the appropriate cells. Final manual checks were performed to verify the consistency of the data across years and fill in possible blanks.

### 3.3. Cluster analysis and development of regional typologies

The analysis of regional typologies based on flows aggregates regions which may lack other shared features (i.e., size, population, economic profile, location, etc.) but have similar 'flow profiles' across the multiple indicators explained earlier. The classification of regions uses a *k*-means cluster analysis, a method that partitions a dataset into groups, in which observations in the same group are as similar as possible and, in different groups, as different as possible. Classification in typologies allows reducing complexity, identifying similarities and differences between groups, and providing a sound basis for comparison. Specifically, the *k*-means technique is preferable for its simplicity, speed and scalability, essential in large datasets. We focus on 2015 and 2020, since variations able to alter the clustering are unlikely to happen every year and a five-year interval may represent the largest changes. Following the previous description, the variables are summarised in Table 2. Except for Send–Receive Balance, they are measured both from the perspective of 'sending' and 'receiving' regions. This results in 13 columns corresponding to these values, forming a matrix with the 329

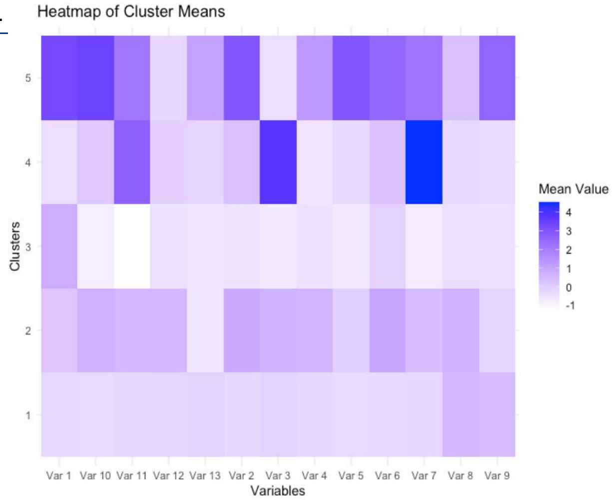
**Table 2.** classification indicators for cluster analysis.

| Dimension | Description | Equation |
|---|---|---|
| Intensity | Total number of partnerships held by a region as coordinator (sender)/as participant (receiver) | $y_i = \sum_i T_{ij}$ |
| Weighted Intensity | Total number of partnerships held by a region as coordinator (sender)/as participant (receiver) weighted by the regional population | $y_i = \frac{\sum_i X_{ij}}{\sum_i X_i}$ |
| Connectivity | Number of distinct destination/origin (coordinator/partner) regions linked to a region | $y_i = \sum_i j$ |
| Interregional Balance | Share of partnerships held by a region as coordinator (sender)/as participant (receiver) in the total number of partnerships held by a country. Considering that a regional share of $X$ has a different meaning depending on the relative size of regions in a country, the share of regional to national partnerships is divided by the share of regional to national population. Values > 1 indicate regions dominating above their size, values < 1 suggest regions lagging behind | $y_i = \frac{\frac{\sum_i T_{ij}}{\sum_i T_i}}{\frac{\sum_{c\_j} T_{c\_ij}}{\sum_{c\_j} T_{c\_j}}}$ |
| Network Selectivity | Number of partnerships held by a region as coordinator (sender) with a main participant (receiver) region as a share of total partnerships/number of partnerships held by a region as participant (receiver) from a main coordinator (sender) region as a share of total partnerships | $y_i = Max\left(\frac{T_{ij}}{\sum_i X_i}\right)$ |
| External Influence | Number of partnerships held by a region as coordinator (sender) with a main participant (receiver) region as a share of total partnerships held by receiver/number of partnerships held by a region as participant (receiver) from a main coordinator (sender) region as a share of total partnerships held by sender | $y_i = \frac{\sum_i T_{ij}}{Max(M_{ji})}$ |
| Send–Receive Balance | Ratio between the number of partnerships held by a region as coordinator (sender) and as participant (receiver). Values vary between 1 and −1, with 0 representing perfectly balanced flows | $y_i = \frac{\sum_i T_{ij} - \sum_i M_{ij}}{\sum_i T_{ij} + \sum_i M_{ij}}$ |

Source: Authors' elaboration.

**Table 3.** Cluster statistics (2015 and 2020), cluster means (2020).

| | 2015 | | 2020 | |
|---|---|---|---|---|
| **Cluster** | **Size** | **Within SS** | **Size** | **Within SS** |
| 1 | 131 | 336.5718 | 115 | 385.3850 |
| 2 | 53 | 333.2068 | 66 | 406.0380 |
| 3 | 74 | 202.1198 | 82 | 228.2539 |
| 4 | 17 | 297.5671 | 8 | 102.8601 |
| 5 | 12 | 388.0501 | 14 | 378.1474 |




NUTS-2 regions. As the analysis cannot cope with empty values, the regions which score zero in every column are removed (meaning that they have no projects whatsoever, either as senders or receivers). In total, 287 regions are analysed for 2015 and 285 for 2020.

Importantly, while the variables used are broadly inspired by metrics from social network analysis, we do not focus on network-level properties but rather on pair-level features of the flows. Instead of mapping or interpreting the entire network, we organise the data into clusters based on these flow characteristics. As a result, the overall structure and summary statistics of the network are not considered in this study. Moreover, while regions vary in size, the aggregation at the regional scale does not result in a modifiable areal unit problem (MAUP) since our focus is on the regional comparison using commonly agreed boundaries (NUTS-2). The sub-regional distribution of the individual project partners does not affect the results, as these are by definition aggregated to create a measure of intensity at the regional level.

The analysis is performed in R, after $z$-standardisation of all the values, and includes tests to determine the ideal number of clusters. Algorithms for the WSS method (based on the total within-cluster sum of squares) and Silhouette method (measuring the quality of fit of each object inside its cluster) were conducted. Within the technically consistent options, a small number of clusters ($n < 3$) does not produce sufficiently relevant differentiations across regions, whereas a high number ($n > 6$) results in too much overlap between clusters in the visualisation, with many 'undecided' regions fitting several groups. Using five clusters returns a good result in both determination methods and was chosen as a balanced option. It produces a visually consistent plot of well-bounded clusters with little overlap. Table 3 shows further descriptive statistics of the clustering. Since presenting a cluster means table for 13 variables would be cumbersome, these are shown in a heatmap, giving an overview of the distinction between clusters and the variables whose mean varies the most.[3] Although statistical significance tests are typically not included in $k$-means clustering, due to its unsupervised nature, lack of outcome variable and distribution assumptions, and focus on minimising within-cluster variance, we still conducted a multivariate analysis of variance in R to confirm the high statistical significance (***) of the clustering (Table 4).

Finally, to further understand what distinguishes the clusters and whether the typologies are meaningful, we look for distinctiveness in indicators which are not part of the analysis but matter for knowledge and innovation. Therefore, after comparing the clusters in terms of the variables used to construct them (where, after all, distinctiveness is expected), we discuss how some differentiation factors vary in each one, namely:

- *Gross domestic product (GDP) per capita in purchasing power standards (PPS)*: to find out whether the differences in the various flow indicators are associated with visible differences in the economic conditions of the regions.
- *Quality of institutions*: to find out whether the specific combination of qualities of each flow profile are related to how the quality of governance is assessed in the regions.
- *Population density*: to explore to what extent regional roles in knowledge networks are associated with

**Table 4.** Multivariate analysis of variance, $k$-means clustering (2020).

| d.f. | Pillai | Approx. $F$ | Num. d.f. | Den. d.f. | Pr(> $F$) | Significance |
|---|---|---|---|---|---|---|
| 1 | 0.79844 | 82.579 | 13 | 271 | < 2.2e–16 | *** |
| Residuals | 283 | | | | | |

density, contributing to the discussion on agglomeration effects.

- *Human resources in science and technology (HRST)*:[4] to assess the relation between the education and job profile of the population and regional knowledge network roles.

## 4. RESULTS

This section presents the flow profiles of regions and their explanatory factors. To understand the context leading to the regional typologies, we briefly highlight key findings of the ESPON IRiE project. First, there is a stable set of countries leading partnership numbers over the study period (Germany, Spain, Italy). Second, capital city-regions dominate intensity and connectivity rankings, except for the drop of London after Brexit. Third, capital dominance varies according to country, depending on the monocentric or polycentric organisation of regional systems (e.g., Paris captures much of the national flows in France, whereas Germany's high-performing regions are better distributed). Fourth, weighting performance according to population helps identify high-performing medium-sized regions. Finally, smaller regions hardly benefit from proximity to top-performing regions, which tend to build networks internally or with partners of similar rank (e.g., Paris-Brussels).

### 4.1. Cluster analysis

First, the clusterings for 2015 and 2020, constructed strictly on the basis of the observed characteristics of the H2020 flows, are visualised in two-dimensional plots generated according to the main explanatory variables (Figure 2). Together, they explain about 64% of the variance.

The analysis returns five groups of different sizes and dispersion around the mean, with little overlap. A first difference emerges from the cluster size: clusters 1–3 contain most regions, while clusters 4 and 5 are smaller and capture somewhat exceptional regions. Cluster 4 includes small and remote regions as well as regions in countries with a single NUTS-2, while cluster 5 gathers large, dominant capital regions. Although smaller, both clusters have larger dispersions around the mean than clusters 1–3, suggesting the presence of outliers. The cluster 4 outlier in the bottom right of both graphs is the French overseas region of Mayotte. Cluster 5 outliers (top left) are London (2015), Brussels and Paris.

Figures 3 and 4 present maps of cluster membership in 2015 and 2020. We observe, for instance, a shift from cluster 1 to cluster 2 in Finish and Spanish regions and south-east France. Although 103 regions have changed clusters between 2015 and 2020, the overall cluster size remains comparable, and the indicators provide a very similar characterisation of all the clusters. Therefore, the 2015 results are mentioned when relevant – for example, to highlight significant cluster changes – but the respective figures are omitted.

The cluster characterisation focuses on the indicators that are most likely to push groups of regions together. The relatively small sample and difficulty to control for other variables that might influence knowledge flows makes conducting regressions redundant; therefore, we generate box plots to compare the variance of each variable in each cluster (Figures 5 and 6). Figure 7 uses box plots to compare how the clusters fare in the four additional indicators explained above, including a comparison of means and interquartile range (IQR) across the clusters (Table 5).

### 4.2. Characterisation of the clusters

#### *4.2.1. Cluster 1: the mainstream strugglers; and cluster 2: the mainstream performers*

These clusters are considered together because their comparison shows important regional differences affecting their performance that would not have been identified otherwise. Clusters 1 and 2 are large groups that together contain 181 NUTS-2 regions (2020). They do not stand out decisively from the averages – as the box plots show, they never score too low or too high in any indicator,

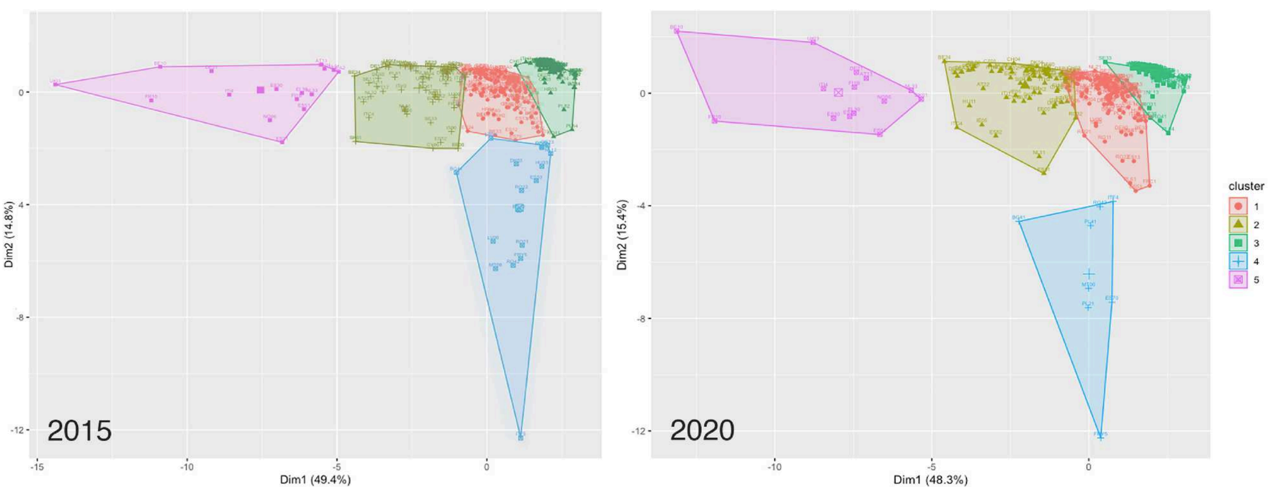



**Figure 2.** *K*-means cluster analysis: bidimensional plot of five clusters, 2015 ($n = 287$) and 2020 ($n = 285$).
Source: Adapted from ESPON IRiE (2022); published with permission.

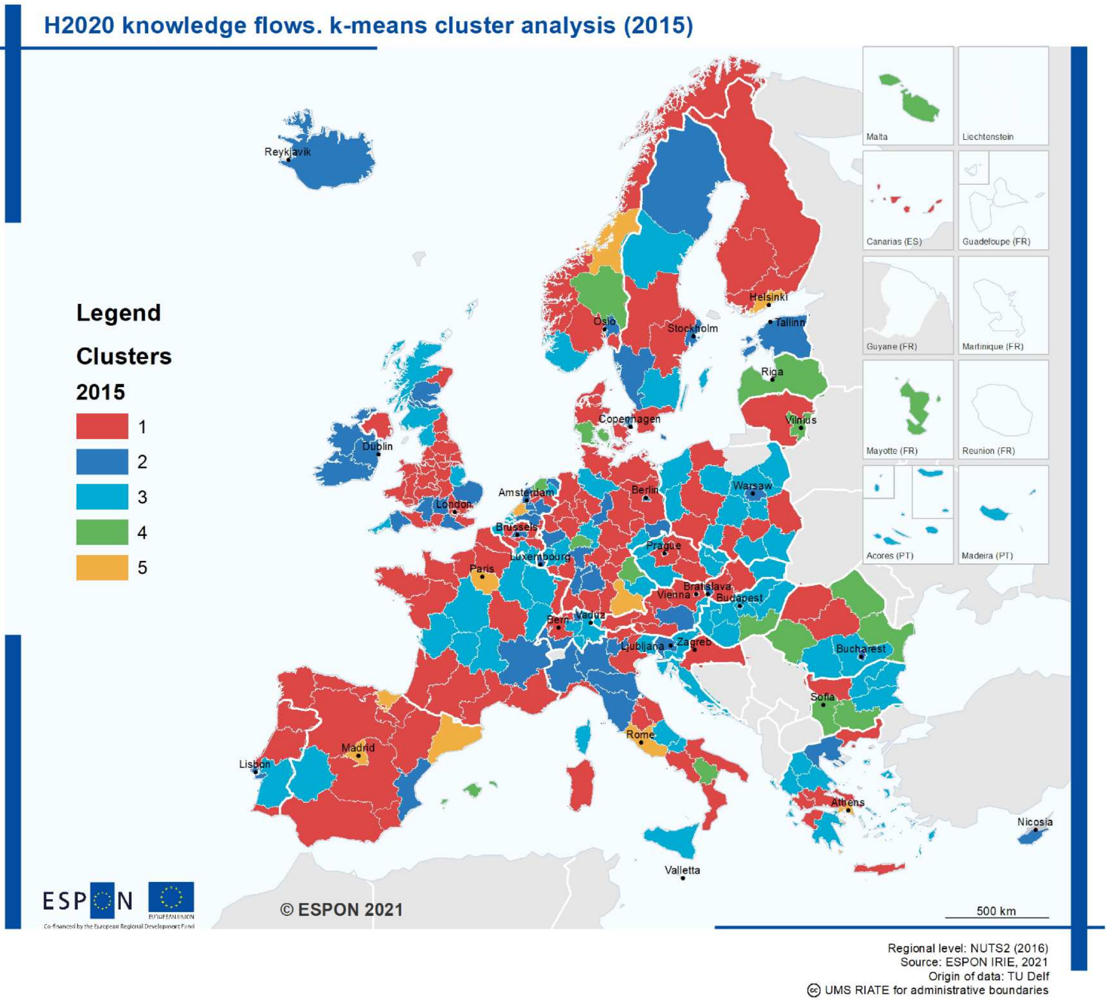



**Figure 3.** Cluster membership of European NUTS-2 regions, Horizon 2020 research networks, 2015.
Source: ESPON IRiE (2022); published with permission.

and the bidimensional plot in Figure 2 shows that they are rather compact. They can be considered 'mainstream' regions with no special differentiating features. However, the flow type of cluster 2 seems to represent a more successful engagement in knowledge networks, ranking higher than cluster 1 in terms of Connectivity, Intensity and Weighted Intensity, as it both coordinates and participates in more partnerships with more regions. Regions in cluster 2 also capture a higher proportion of their national flows than cluster 1 (Interregional Balance), ranking above the average, meaning that in the national context they host more knowledge flows than their relative population size would predict. Cluster 1 regions perform more poorly, ranking below the average in all these indicators, and visibly lower than cluster 2. Cluster 2 regions are also slightly less dependent on a single preferred partner (Network Selectivity) and have a bigger influence on the flows of their main partner than cluster 1 (External Influence). This is the case both for 'sender' and 'receiver' roles. While clusters 1 and 2 are more oriented to coordination than participation, cluster 2 regions rank slightly better as coordinators.

The regions are well distributed across Europe. However, there is a larger presence of Eastern European and Baltic regions in cluster 1 (21 regions versus eight in cluster 2). Many Scandinavian and Spanish regions progressed from cluster 1 to cluster 2 between 2015 and 2020. Notably, despite the differences across basic indicators, the largest countries (Germany, France, Italy) have several regions in both clusters, suggesting a level of regional imbalance. In summary, within the mainstream 'unexceptional' regions, clusters 1 and 2 establish a visible contrast between struggling and performing regions.

### *4.2.2. Cluster 3: the silent partners*

Cluster 3 regions are those that do not coordinate many projects and are mostly partners in other networks, thus presenting an unbalanced send–receive ratio. Faring poorly in project coordination can be compensated by strong participation roles in several projects with various regions, but becomes problematic when other indicators also present negative results. Indeed, cluster 3 regions score the lowest in several other dimensions. All the regions that score highly as coordinators also fare well as partners, although there are obviously many more regions lacking coordinator than partner roles. In addition, these regions have a high dependence on a main project partner, as the network selectivity box plot shows.

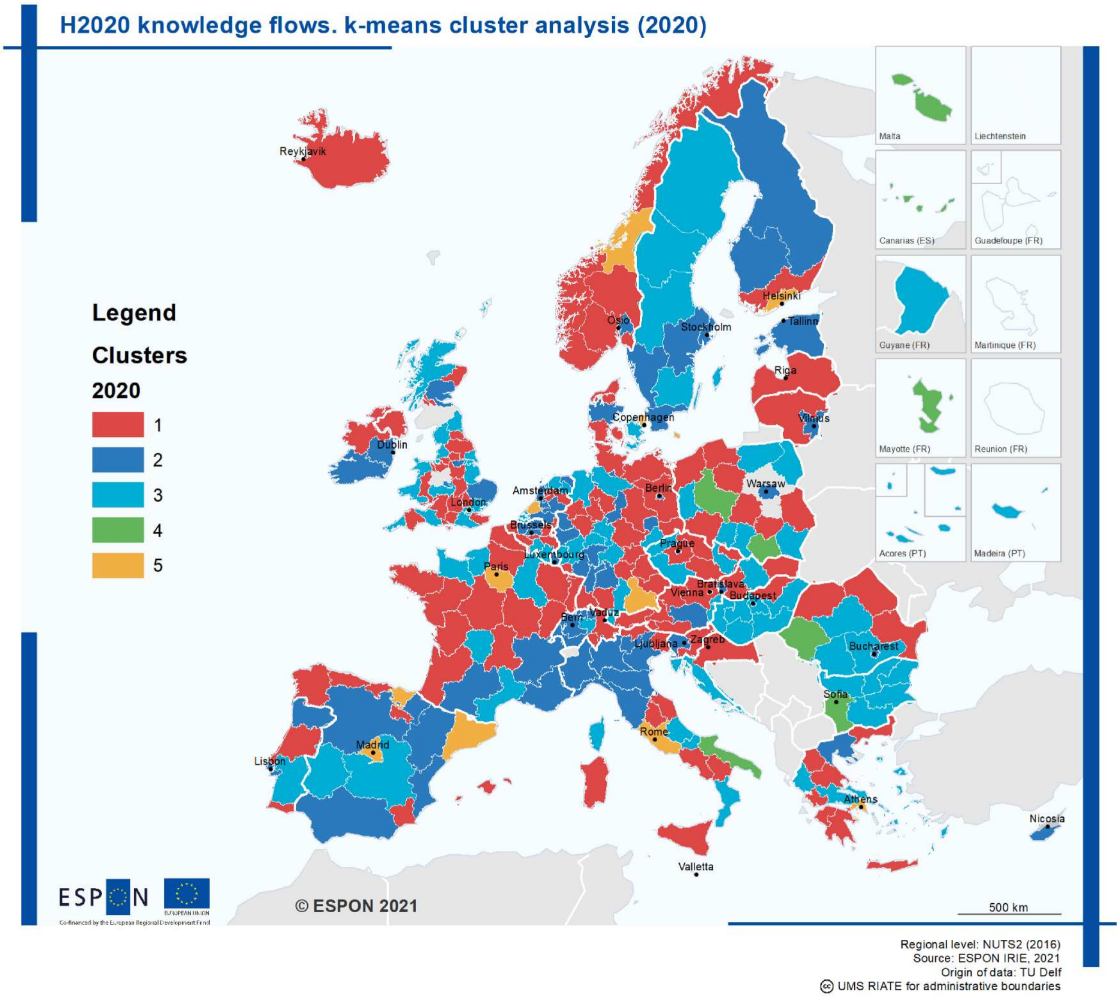



**Figure 4.** Cluster membership of European NUTS-2 regions, Horizon 2020 research networks, 2020.
Source: ESPON IRiE (2022); published with permission.

There is some mobility across clusters, though, illustrating network coordination opportunities for some regions that find a way up. Of the 75 regions in cluster 3 in 2015, 25 left in 2020 suggesting that a good track record as a project partner can create an incentive to adopt coordination roles later with a stable set of partners. Not all regions benefit from coordination opportunities, as 33 new regions joined cluster 3 between 2015 and 2020, including 11 UK regions that lost all coordinator roles. Country-level patterns appear for Hungary (six out of eight regions in cluster 3) and Bulgaria (four out of six). The case of Sweden, with four regions lacking coordination but still performing well at the national level, is unusual. These are sparsely populated regions (400,000–800,000 inhabitants); yet, the Stockholm region captures nearly 60% of all project coordination roles in the country.

### *4.2.3. Cluster 4: the constrained dependents*

Cluster 4 contains a small group of regions that stand out for specific reasons and reflect localised, specialised, small-scale networks formed around a relatively stable group of regions. This cluster scores similarly to cluster 3 in Connectivity, Intensity and Weighted Intensity, meaning that they rank as poorly as project coordinators and only slightly better as partners. Interestingly, their interregional balance is high, at the level of cluster 1. If they underperform in terms of project numbers and are able to take a high proportion of partnerships nationally, some should be leading regions in small or low-performing countries, and indeed the capital regions of Bulgaria, Malta, and Latvia and Lithuania (2015) are in cluster 4.

The outstanding feature of cluster 4 is the level of dependence on a single preferred partner. This is revealed by the Network Selectivity box plot as coordinators (when they coordinate, they turn heavily to a main project partner) and the External Influence results as partners (when they join a network, it tends to come from a preferred coordinating partner). Their External Influence as coordinators is also high, meaning that their coordination is very significant for the preferred partners. These regions either specialise in a specific set of research areas or have no access to the larger project networks managed by others, notably those led by 'superstar' regions in cluster 5. They are likely to be island and/or low-density regions. From 2015 to 2020, the number of regions in cluster 4 decreased and visibly congregated in Eastern Europe.


**Figure 5.** Box plots of differences between clusters, $k = 5$, sender–receiver, 2020: Intensity, Weighted Intensity, Connectivity and Send–Receive Balance.
Source: Adapted from ESPON IRiE (2022); published with permission.

### *4.2.4. Cluster 5: the superstars*

Cluster 5 gathers the large players in European research networks, such as Paris, Brussels, Rome, London or Madrid. A first signal differentiating this group is stability; all the regions in cluster 5 in 2015 remain in 2020, with the new additions of Vienna and Copenhagen. Dominant players that reach this selective group do not lose that position easily. They are mostly large, densely populated regions that host not only the main research institutions, but also the economic powerhouses able to manage large projects and develop research outputs, and the places where policy decisions are made. Cluster 5 regions score the highest in (Weighted) Intensity and Connectivity, both as coordinators and partners. They are also top scorers in Interregional Balance, capturing more flows nationally than their relative population size would predict. They have a low Network Selectivity, meaning that they have diversified connections rather than relying on preferred partners. But they have a high External Influence, especially as coordinators, showing their key role in the incoming flows of other regions. Finally, their Send–Receive Balance is strongly turned to coordination, despite high scores as participants.

Two outsiders in this cluster are Trøndelag in Norway and the Basque Community in Spain. These are small, non-core regions that do not fit most of the features typical of cluster 5, but mimic the performance of the top regions in many knowledge flow indicators. Although the unusual profile of these regions warrants further study, some

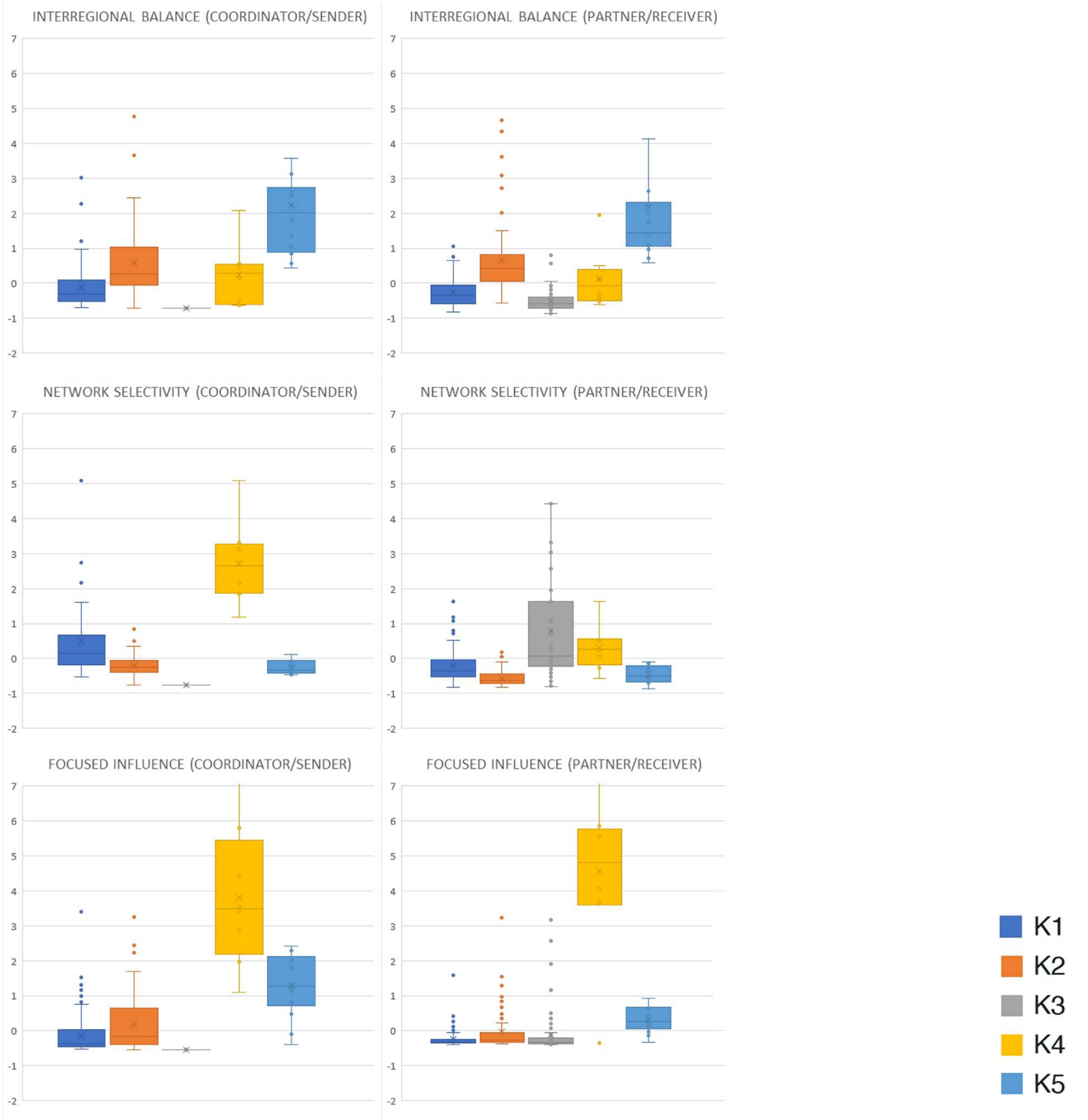



**Figure 6.** Box plots of differences between clusters, $k = 5$, sender–receiver, 2020: Interregional Balance, Network Selectivity and External Influence.
Source: Adapted from ESPON IRiE (2022); published with permission.

hypotheses can explain their outstanding performance. Trøndelag is a sparsely populated region that seems to benefit from an effective RIS relying on collaboration networks, learning clusters that enhance scientific excellence and high-quality institutions with strong public support to R&D as well as private involvement in international research. The Basque Country is a post-industrial region that has become one of Spain's most prosperous areas. Beyond its shift towards the knowledge economy, this region's performance may relate to its connections with the private (industrial) sector, strong presence of R&D companies and public investment in innovation, and lifelong learning decentralised policies.

## 5. DISCUSSION

Our research identifies the various ways in which European regions engage in knowledge networks, represented here H2020 partnerships, confirming the unequal distribution of access to these networks and the variety of roles played by regions. Results of past research that are arguably compatible with our findings include the role of a shared language and cultural background, familiarity between partners that enables trust, and well-aligned regulatory frameworks that promote a shared vocabulary and stability. This is why the strongest partnership pairs are between partners in the same region, or culturally

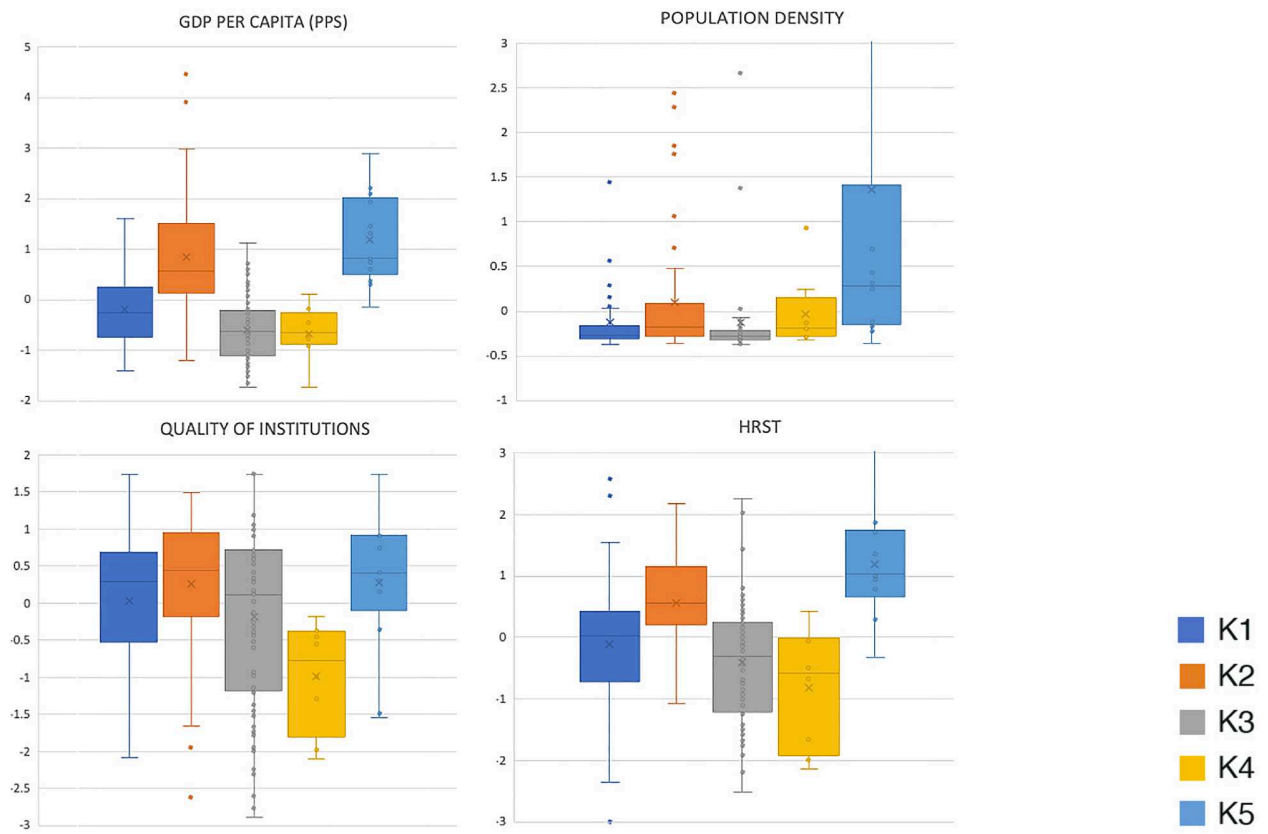



**Figure 7.** Box plots of differences between clusters, $k = 5$, 2020. Additional variables variation.
Source: Adapted from ESPON IRiE (2022); published with permission.

proximate regions. This section discusses further factors that differ across our regional typologies and play a relevant role in their flow profile, although the scope of this paper does not allow definitive claims about how they interact to determine knowledge flows.

The analysis suggests the positive impacts of size and density. The best performing regions concentrate or have easy access to capital, knowledge and information flows; a diverse, educated and specialised labour force ('sharing, matching and learning') as well as high-level infrastructure and diverse urban functions. Hence, large and dense regions dominate most rankings (cluster 5) and have the strongest partnerships between actors. Also, the comparison of the two first clusters reflects their contrasting size and density, together with differences in GDP per capita and HRST (despite outliers). Conversely, low-density regions (e.g., cluster 3), unless they are strongly specialised, struggle to build the critical mass needed for performance. Interestingly, the geographical proximity to 'superstar' regions does not reflect in a flow pattern or advantages in flow intensity or connectivity; yet, this is maybe visible at the smaller NUTS-3 scale within regions. But geographical and spatial factors matter, as shown by consistent trends of upward-moving regions in Western Europe, poorly performing regions in Eastern Europe, and contrasts between polycentric and monocentric countries, where capital regions capture most national flows, at the expense of the performance of other regions.

Furthermore, the analysis highlights the role of institutional quality in the performance of regions in knowledge networks. Regions with high-quality institutions and policy stability make it easier for actors to foresee outcomes and distribute resources fairly and enhance trust and dialogue between research and government bodies.

**Table 5.** Summary statistics of additional box plots (2020).

| | GDP per capita | | Population density | | Quality of institutions | | HRST | |
|---|---|---|---|---|---|---|---|---|
| | Mean | IQR | Mean | IQR | Mean | IQR | Mean | IQR |
| K1 | −0.203 | 0.972 | −0.129 | 0.140 | 0.031 | 1.210 | −0.117 | 1.138 |
| K2 | 0.830 | 1.398 | 0.096 | 0.374 | 0.265 | 1.131 | 0.568 | 0.936 |
| K3 | −0.607 | 0.906 | −0.125 | 0.105 | −0.189 | 1.894 | −0.414 | 1.473 |
| K4 | −0.663 | 0.623 | −0.027 | 0.436 | −0.989 | 1.414 | −0.825 | 1.774 |
| K5 | 1.179 | 1.525 | 1.355 | 1.565 | 0.282 | 1.014 | 1.181 | 1.089 |

Generally, higher institutional quality aligns with better performance in knowledge networks, although cluster 5 scores lower than clusters 1 and 2, meaning that large and complex metropolitan regions may experience governance bottlenecks which are less exacerbated in smaller regions. Moreover, the large variance of this indicator in cluster 3 reveals that some regions, despite being in countries with good institutional quality, remain trapped in low innovation capacity. However, institutional quality can improve over time; the 2015–2020 comparison shows greater upward mobility opportunities in low-performing regions than downward mobility in the best-performing ones.

Another aspect revealed by the cluster analysis is the coexistence of hard and soft approaches to network leadership. Heavyweight regions gather a large variety of research institutions and decision-making centres on knowledge policy. In particular, capital city regions are subject to historical self-reinforcement of economic and political power functions that gravitate towards existing ones, benefiting from interaction. Smaller peripheral regions have softer approaches, often based on a more selective approach to preferred partners. For example, clusters 1 and 2 have a larger dispersion around the mean in HRST than cluster 5, with positive outliers arguably suggesting smaller but highly intensive and specialised knowledge areas. The levels of dependence of cluster 4 may reveal localised and specialised networks formed around a stable set of partners. Other approaches include hosting large universities and developing broad quadruple-helix ecosystems and/or city-region-university agreements. For instance, an original finding of cluster 5 was the identification of overperforming outliers well connected to external networks and benefiting from entrepreneurial policies nurturing domestic R&D ecosystems, which helps them overcome regional structural or geographical disadvantages.

These divergent approaches show path dependency in the evolution of knowledge flows. Regions with a high number of coordination roles also accumulate more partner roles and perform better. Top performers gain stability from a positive track record, with no changes at the top. On the opposite, low-end performers show volatility. Regions that depend on single partners remain in smaller, less diverse and local networks. For these regions, diversifying sectors and partners feeds positive results and upward mobility is visible over time. However, paths can be heavily disrupted by external shocks. Brexit was a key trigger of London's performance drop, while the results of EU regions with a comparable size improved in the same period. Brexit has also dramatically affected other UK regions (11 lost all coordination roles, connectivity and intensity less than halved).

## 6. CONCLUSIONS

This paper aimed to characterise the circulation of knowledge flows between European regions through a typological classification using a cluster analysis. This approach provided a comprehensive analysis of all European regions using the most recent data available, thereby complementing predominant case study-based approaches. This allows a broader comparison between regions and reveals similarities, differences and trajectories over time that encourage further research on specific cases. Finding similar patterns in apparently unrelated regions is an innovative approach that helps identify explanatory factors that influence flows and provides an opportunity to share lessons and practices between regions which would otherwise not engage in mutual learning. The paper moves beyond the assumption that the key measure of positive performance implies flow intensity to develop a multidimensional 'flow profile' whose components reveal how much different aspects of flows matter for different regions. Indeed, our literature review identified several claims regarding the relevance of connectivity, national imbalances, diversification of fields and partners, among other aspects. This paper operationalises them as indicators applied to all European regions.

The cluster analysis revealed a set of distinctive typologies, obtained from the analysis of these indicators. Still, the clustering does suggest associations with indicators on density, economy, institutions, and employment which strengthen the relevance of our approach. Regions have been grouped into five clusters, two large ones that differ mainly in their overall performance, and three clusters with unique characteristics: lack of network coordination roles, dependence on single partners and network dominance, both at national and European scales. The external indicators and, often, geographical divisions respond accordingly to this differentiation.

The study has several limitations that could be addressed in future research. A first limitation is the potential descriptive nature of the relations detected, unavoidable when analysing 329 regions. Regions are unique and while this paper paints a broad picture of how they relate to each other in knowledge networks, it cannot consider all regional specificities. However, we provide a sound foundation for future studies of representative cases based on the different types that can address this limitation. Second, H2020 networks only tell part of the story of knowledge flows and innovation potential. More research is needed to capture knowledge flows among companies, the thematic scope of collaborations, or product innovation, for example. Third, the methodological option to overemphasise the value of coordinator over partner roles, important to streamline the data processing and to reflect on the balance between different roles, may exaggerate the role of heavyweight coordinators (e.g., cluster 5) and neglect the valuable links built between other partners. An alternative methodology could focus on measuring all partner-to-partner flows and obtain insights on how every region fares in the overall knowledge exchange network. However, such an approach would be more limited to intensity and connectivity measures, and the cluster differentiation based on network selectivity, external influence and coordinator-participant (send–receive) balance would be restricted. Finally, the research does not show how H2020 partnerships actually produce knowledge that fosters regional innovation, for example, how it spills over from the consortia members to other actors and activities beyond those projects. The impacts of these partnerships require further investigation.

By grouping regions according to their interregional knowledge flow features, the research provides a new methodological perspective to identify common drivers and barriers to performance in knowledge networks, supporting policy formulation beyond territorial boundaries. The study also points to the need for regional policymakers to share practices and lessons to address the different roles played by a region in knowledge networks and their unequal levels of access and participation.

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## DISCLOSURE STATEMENT

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## NOTES

1. For a vast collection of publicly available project results, see https://archive.espon.eu/programme/projects/espon-2020/applied-research/interregional-relations-europe/.
2. Minimum and maximum partnership size in projects starting in 2015 and 2020.
3. For brevity, the heatmap and significance analysis refer to the 2020 clustering. The 2015 results are very similar and available from the authors on request.
4. HRST is a measure promoted by the European Commission of people with tertiary education and/or employed in science/technology areas, 'actually or potentially devoted to the systematic generation, advancement, diffusion and application of scientific and technological knowledge' (Eurostat, n.d.).

## ORCID

*Rodrigo Viseu Cardoso* http://orcid.org/0000-0001-8989-9160
*Constance Uyttebrouck* http://orcid.org/0000-0002-1902-4358
*Marcin Dąbrowski* http://orcid.org/0000-0001-6775-0664

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